Credit EDA Case Study

by

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Introduction

- This case study aims to give you an idea of applying EDA in a real business scenario. In this case study, apart from applying the techniques that you have learnt in the EDA module, you will also develop a basic understanding of risk analytics in banking and financial services and understand how data is used to minimize the risk of losing money while lending to customers.

Business Understanding - 1

- The loan providing companies find it hard to give loans to the people due to their insufficient or non-existent credit history. Because of that, some consumers use it as their advantage by becoming a defaulter. Suppose you work for a consumer finance company which specialises in lending various types of loans to urban customers. You have to use EDA to analyse the patterns present in the data. This will ensure that the applicants capable of repaying the loan are not rejected.
- When the company receives a loan application, the company has to decide for loan approval based on the applicant’s profile. Two types of risks are associated with the bank’s decision:
- If the applicant is likely to repay the loan, then not approving the loan results in a loss of business to the company
- If the applicant is not likely to repay the loan, i.e., he/she is likely to default, then approving the loan may lead to a financial loss for the company.

Business Understanding - 2

The data given below contains the information about the loan application at the time of applying for the loan. It contains two types of scenarios:

- **The client with payment difficulties:** he/she had late payment more than X days on at least one of the first Y instalments of the loan in our sample,
- **All other cases:** All other cases when the payment is paid on time.

When a client applies for a loan, there are four types of decisions that could be taken by the client/company):

1. **Approved:** The Company has approved loan Application
2. **Cancelled:** The client cancelled the application sometime during approval. Either the client changed her/his mind about the loan or in some cases due to a higher risk of the client he received worse pricing which he did not want.
3. **Refused:** The company had rejected the loan (because the client does not meet their requirements etc.).
4. **Unused offer:** Loan has been cancelled by the client but on different stages of the process.

In this case study, we will use EDA to understand how consumer attributes and loan attributes influence the tendency of default.

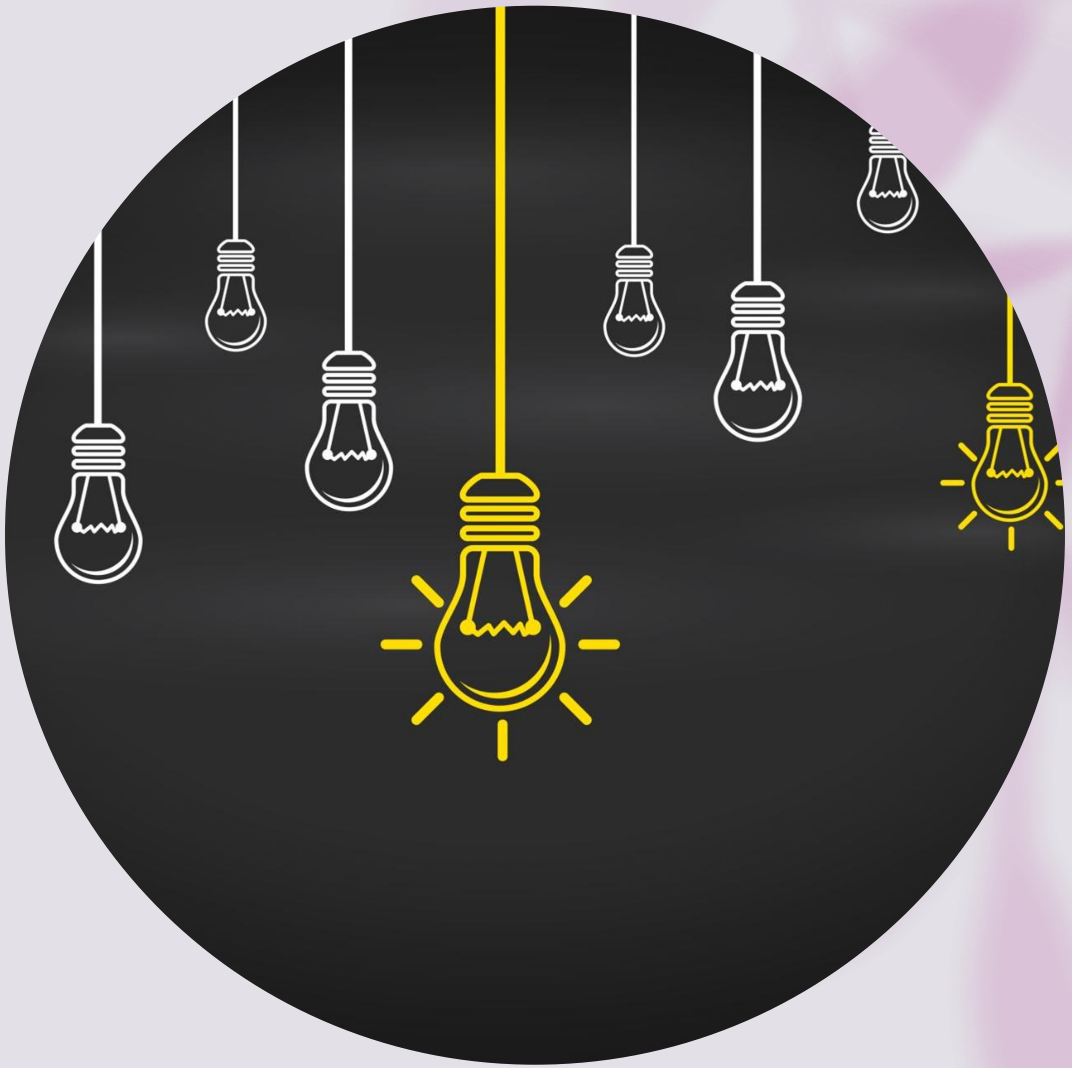
Business Objectives

- This case study aims to identify patterns which indicate if a client has difficulty paying their installments which may be used for taking actions such as denying the loan, reducing the amount of loan, lending (to risky applicants) at a higher interest rate, etc. This will ensure that the consumers capable of repaying the loan are not rejected. Identification of such applicants using EDA is the aim of this case study.
- In other words, the company wants to understand the driving factors (or driver variables) behind loan default, i.e., the variables which are strong indicators of default. The company can utilize this knowledge for its portfolio and risk assessment.
- To develop your understanding of the domain, you are advised to independently research a little about risk analytics - understanding the types of variables and their significance should be enough).

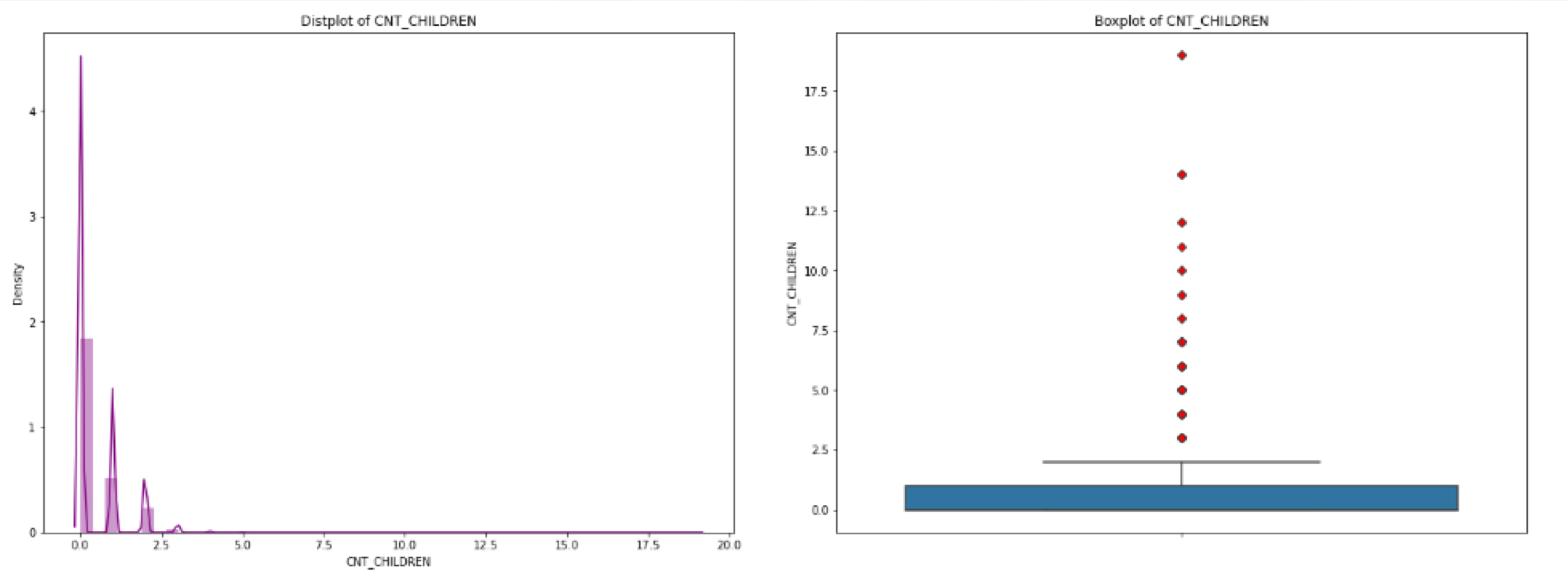
Data Understanding

- This dataset has 3 files as explained below:
- *1. 'application_data.csv'* contains all the information of the client at the time of application.
  The data is about whether a **client has payment difficulties.**
- *2. 'previous_application.csv'* contains information about the client's previous loan data. It contains the data whether the previous application had been **Approved, Cancelled, Refused or Unused offer.**
- *3. 'columns_description.csv'* is data dictionary which describes the meaning of the variables.

Analysis of information of the client at the time of application

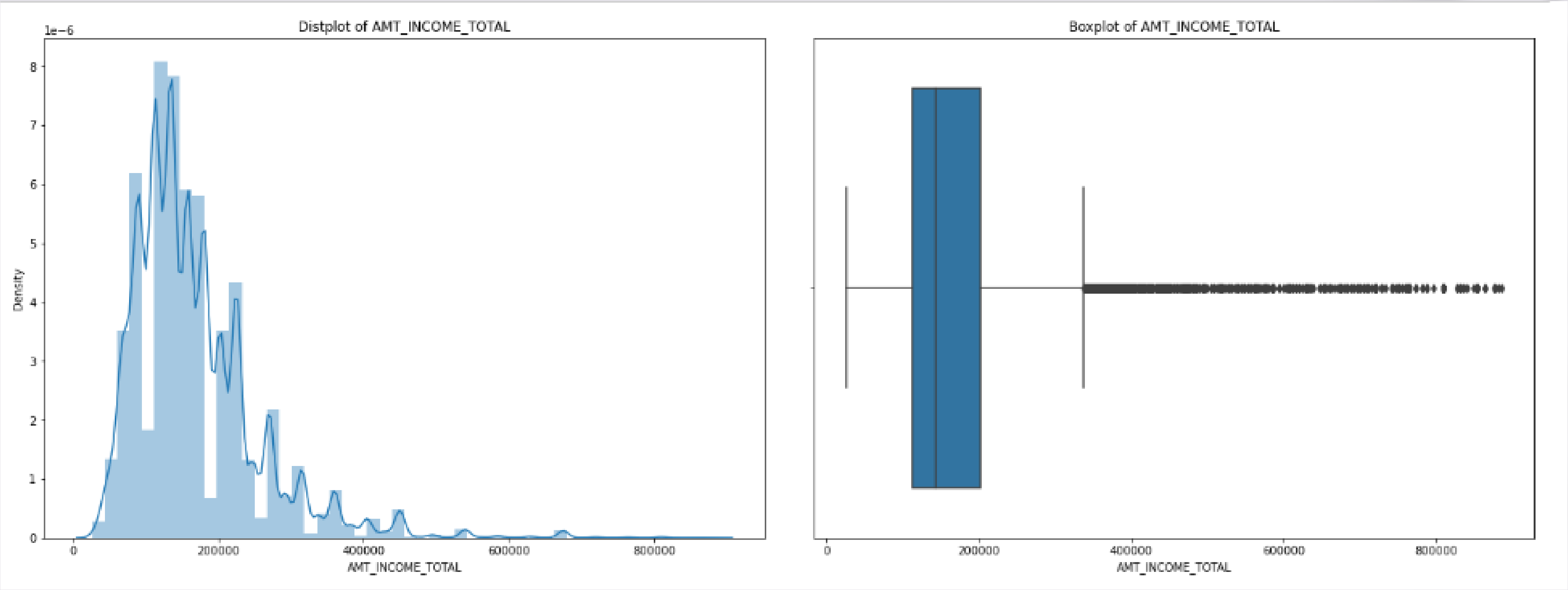


Outlier analysis



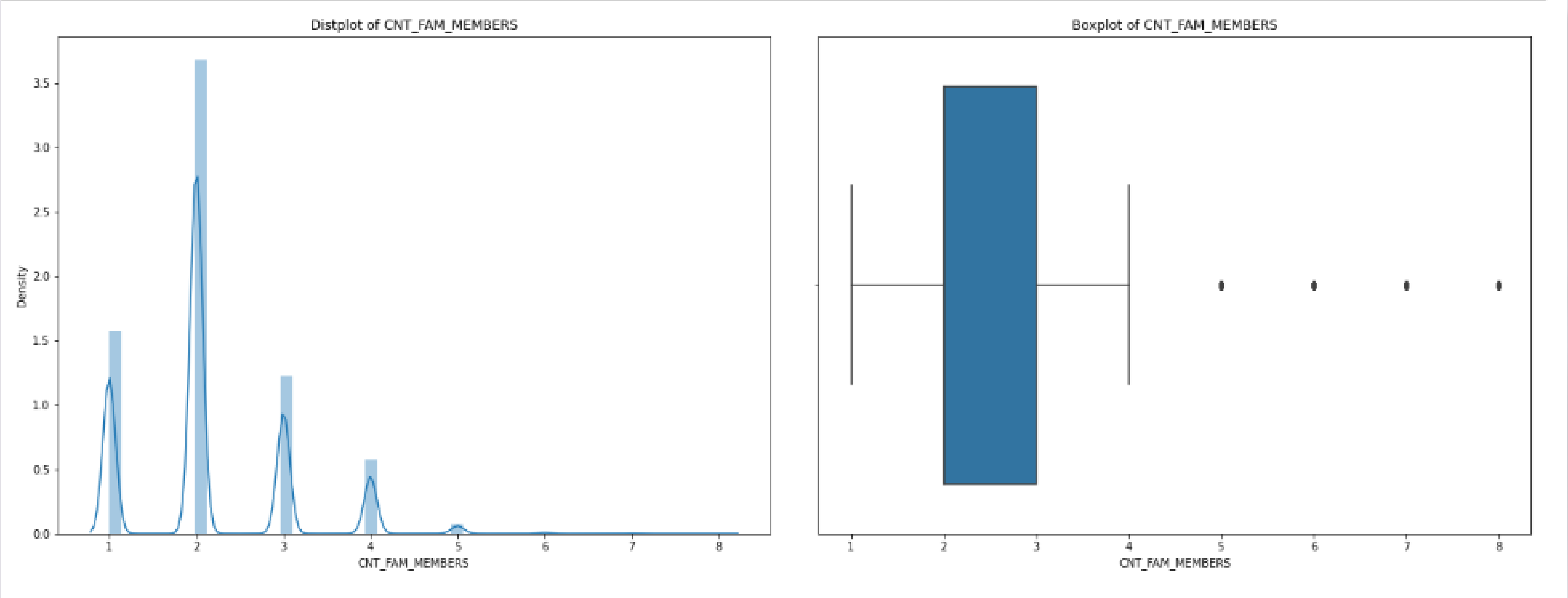
Analysis of `CNT_CHILDREN`

- \- Looking at the data, we can see that above 7 children, the count of applicants are very minimal (2 or 3 in each category)
- \- Also, looking at the observation data for applicants with 10 children, the applicants are only 31 and 41 years respectively. This seems a one-off scenario and can be treated as an outlier
- \- Both distplots and boxplots clearly show the values above 2.5 as being outliers
- \- Applicants with 3 or more children are outlier cases



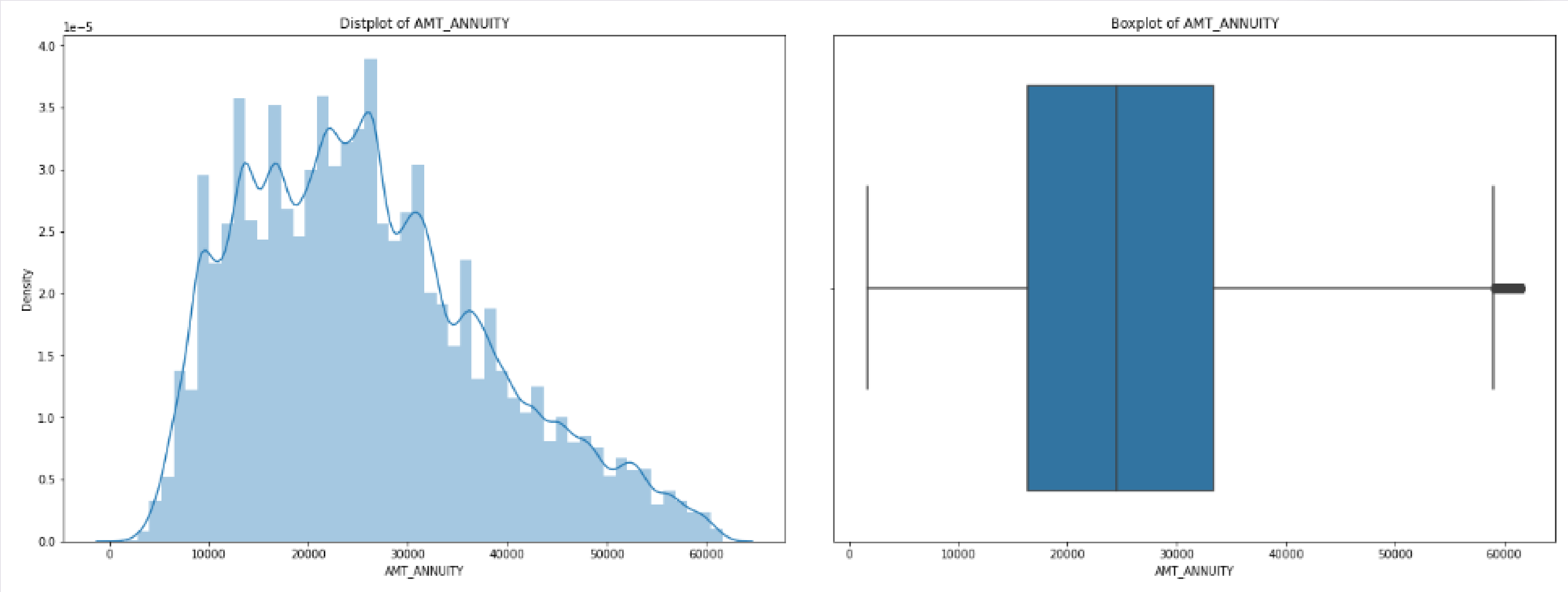
Analysis of `AMT_INCOME_TOTAL`

- - Applicants with Income above 900K (99.9% value) are outliers



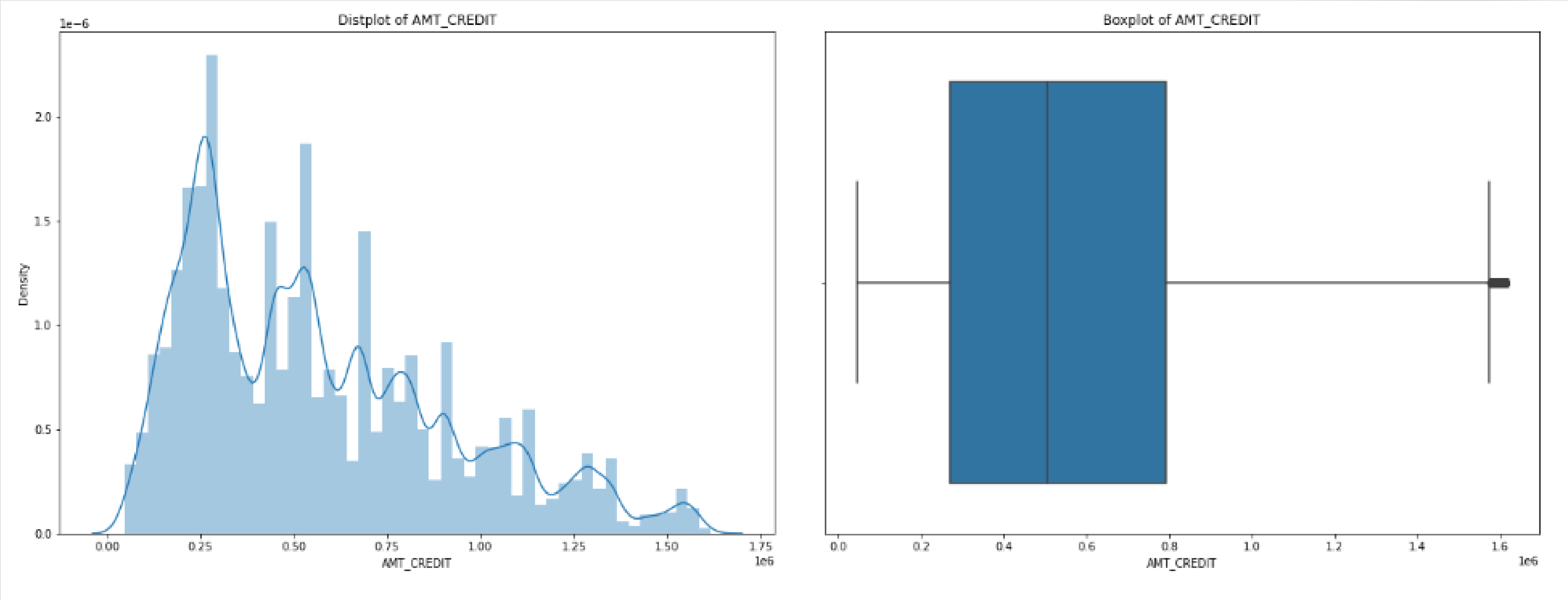
Analysis of \`CNT_FAM_MEMBERS\`

- \- Applicants with 5 or more family members are clearly outliers



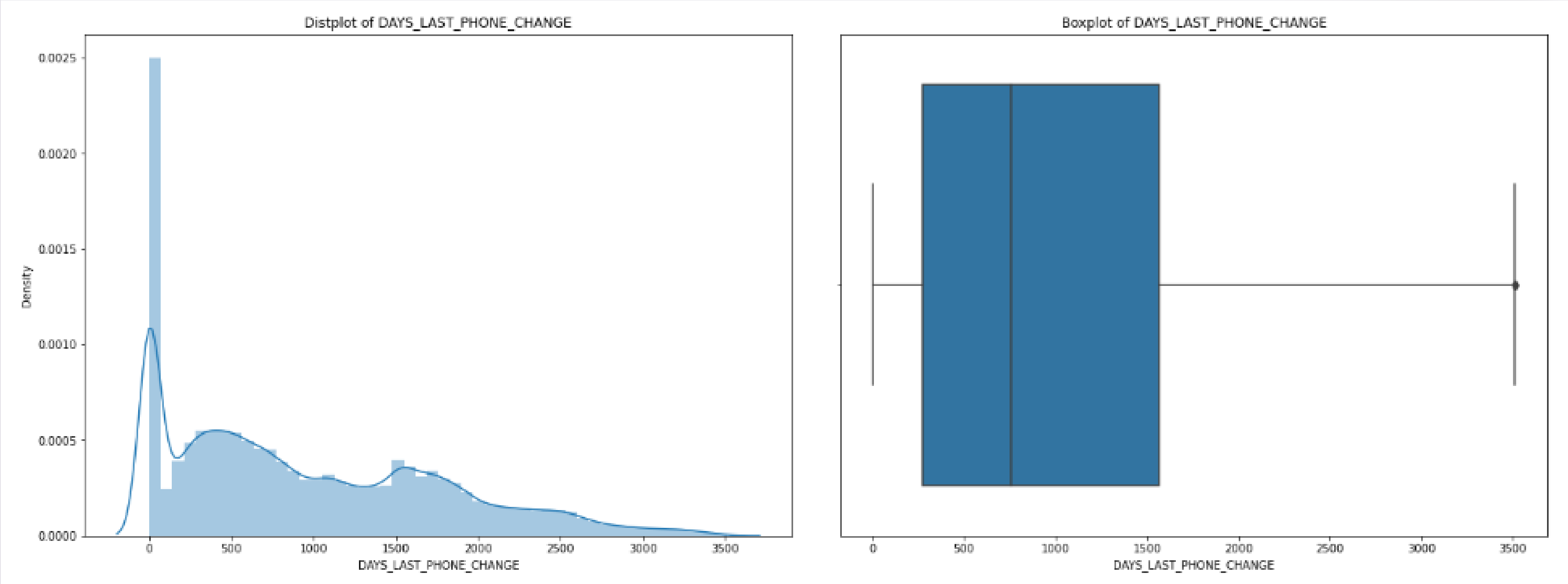
Analysis of `AMT_ANNUITY`

- \- As observed from distplot and boxplot, the outliers tend to exist after 61704
- \- Applicants with `AMT_ANNUITY` above 61704 (calculated using IQR) are outliers



Analysis of `AMT_CREDIT`

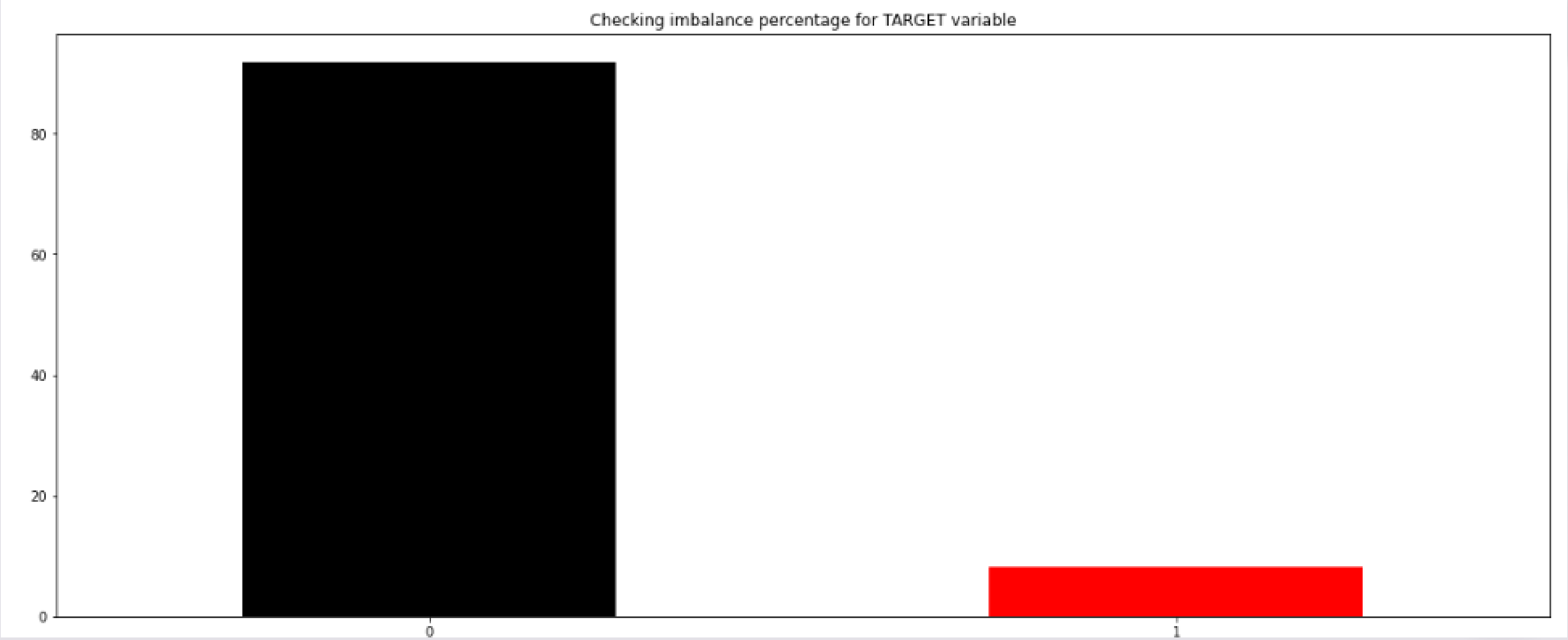
- As observed from displot and boxplot, the outliers tend to exist after 1616625.0
- Applicants with `AMT_CREDIT` above 1616625.0 (calculated using IQR) are outliers



Analysis of \`DAYS_LAST_PHONE_CHANGE\`

- \- As observed from displot and boxplot, the outliers tend to exist after 3514.0
- \- Applicants with \`DAYS_LAST_PHONE_CHANGE\` above 3514.0 (calculated using IQR) are outliers

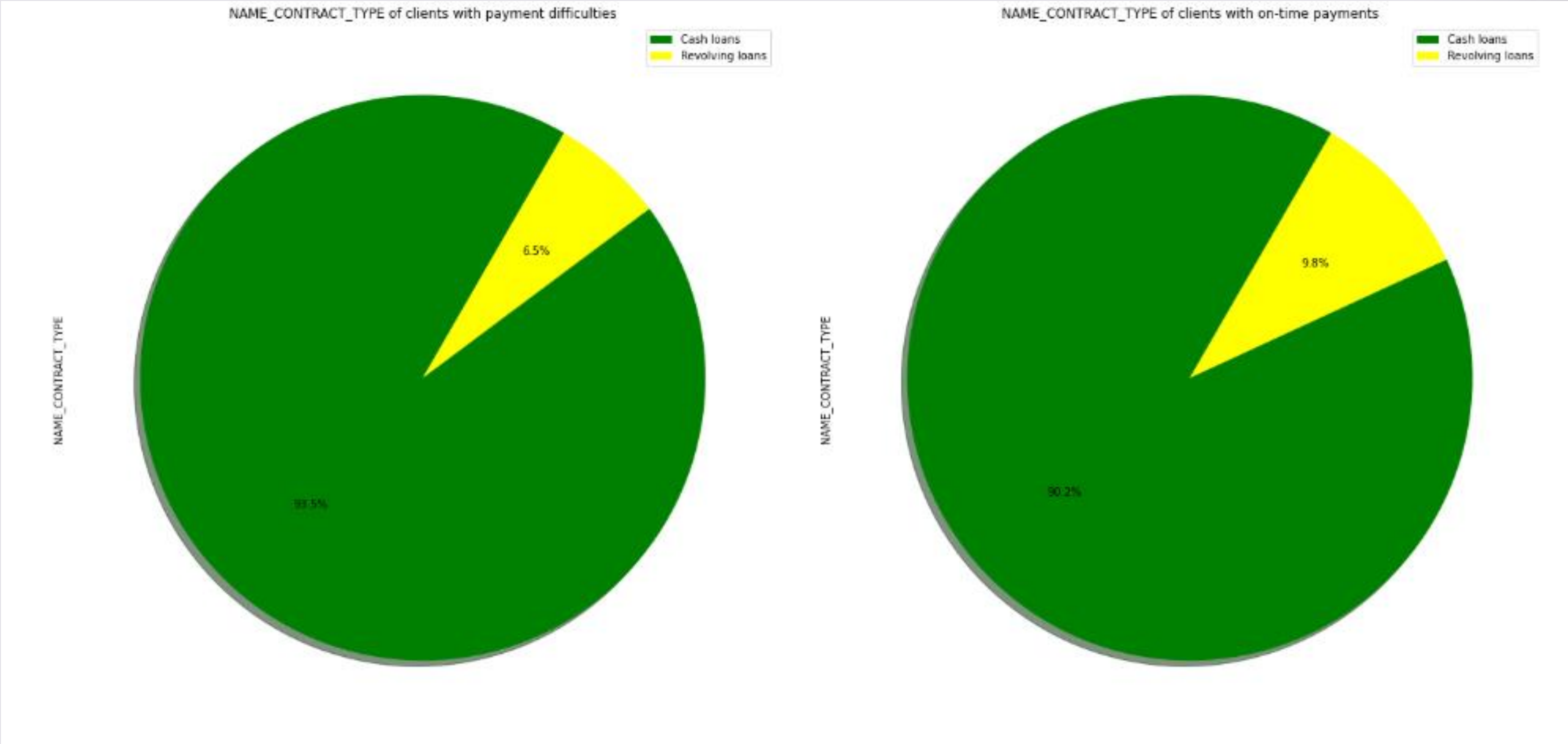
Checking imbalance for Target



Analysis of imbalance for `TARGET`

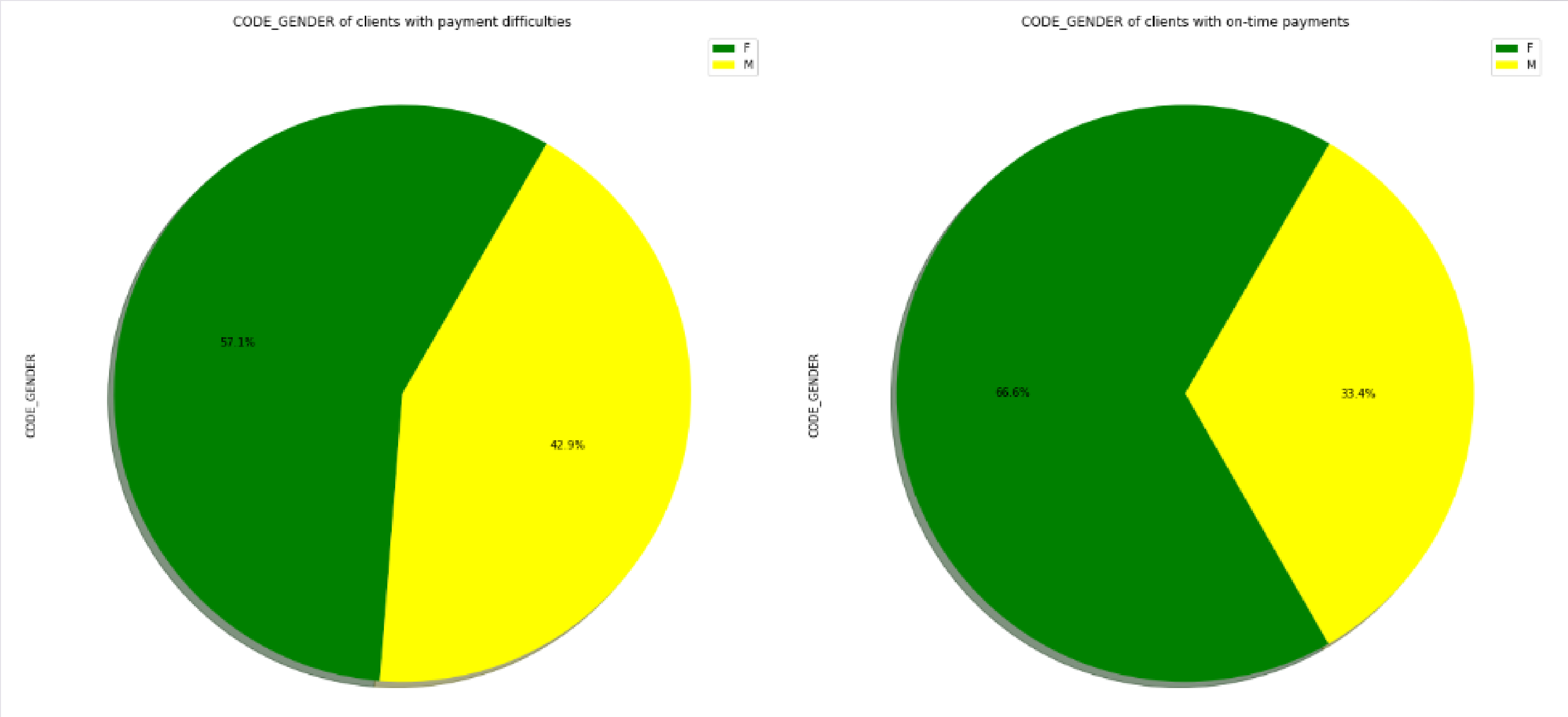
- \- We have imbalance in `TARGET` variable based on the % of observations
- \- `TARGET` value 1 represents client with payment difficulties (he/she had late payment more than X days on at least one of the first Y installments of the loan). This is only 8.07% of the data
- \- `TARGET` value 0 represents all other cases than 1. This is 91.93% of the data

Univariate analysis of categorical variables



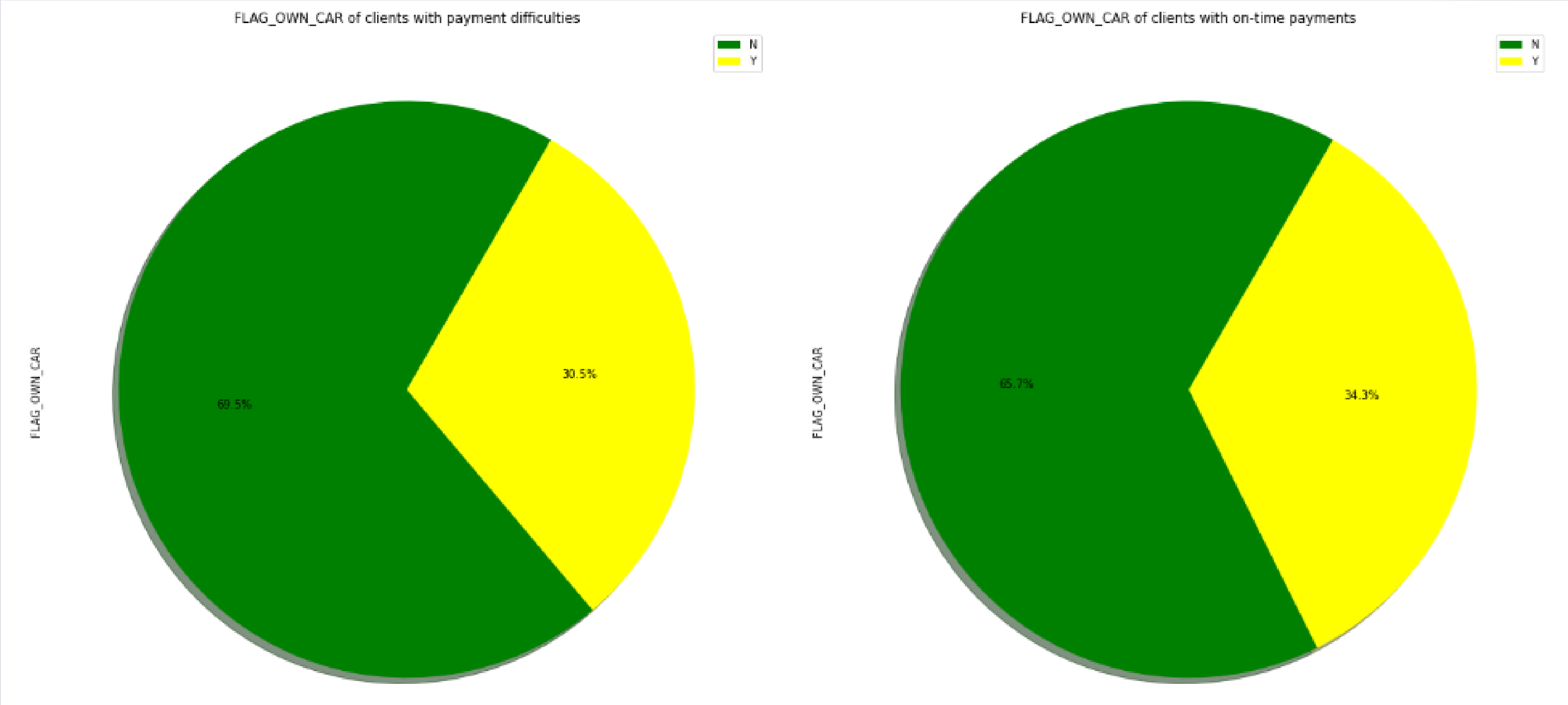
Analysis of `NAME_CONTRACT_TYPE`

- - `NAME_CONTRACT_TYPE` column does not provide any conclusive evidence in favor of clients with payment difficulties OR on-time payments



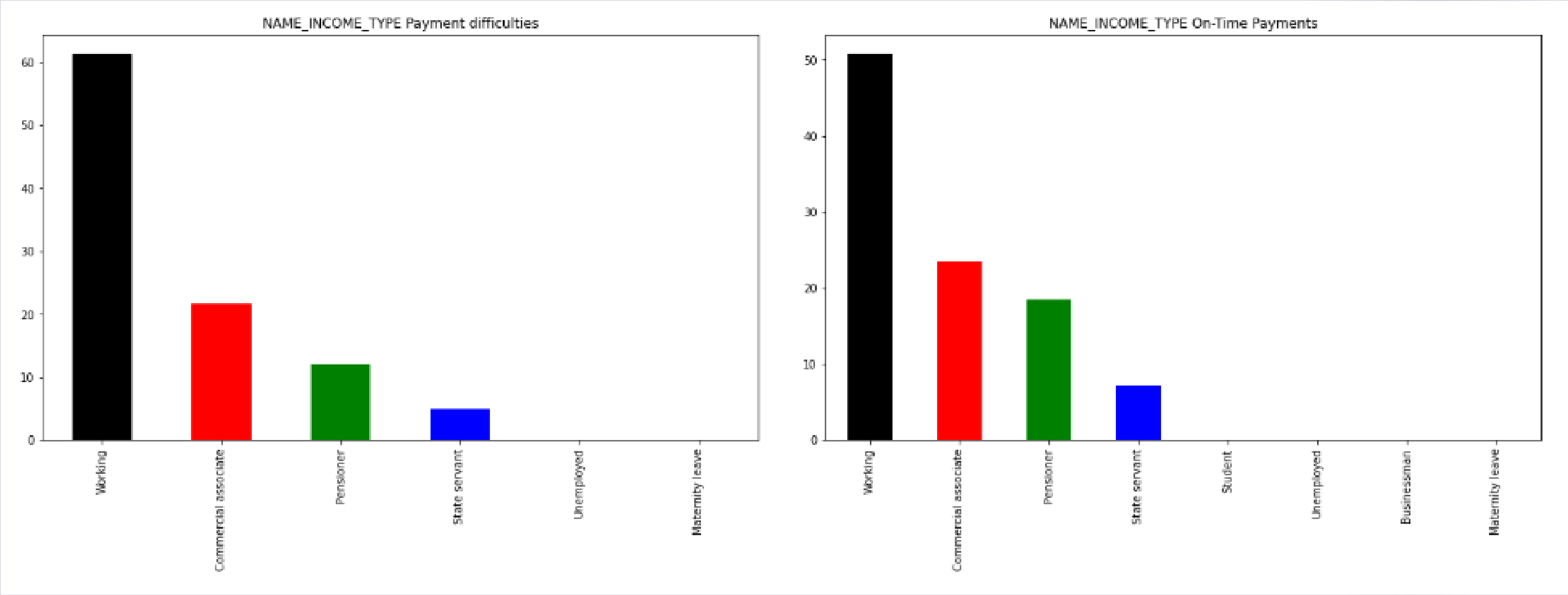
Analysis of `CODE_GENDER`

- - `CODE_GENDER` column provides a weak inference that "Male" clients have more payment difficulties



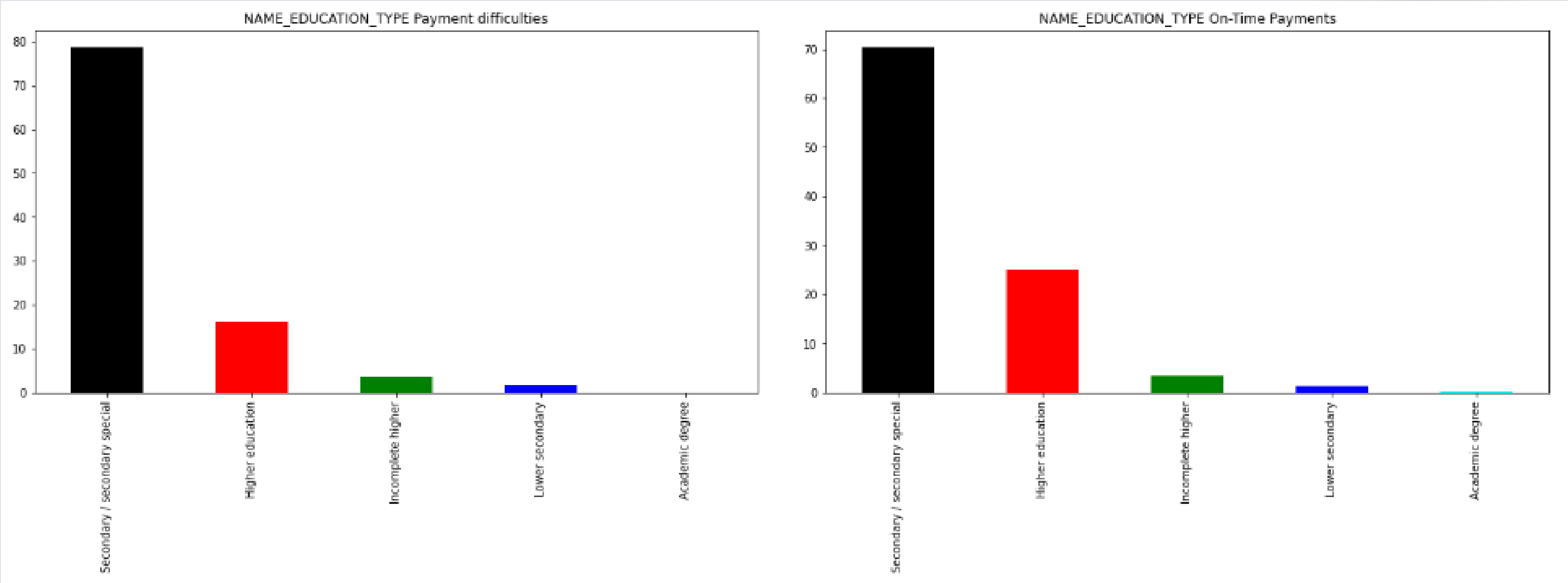
Analysis of `FLAG_OWN_CAR`

- - `FLAG_OWN_CAR` column does not provide any conclusive evidence in favor of clients with payment difficulties OR on-time payments



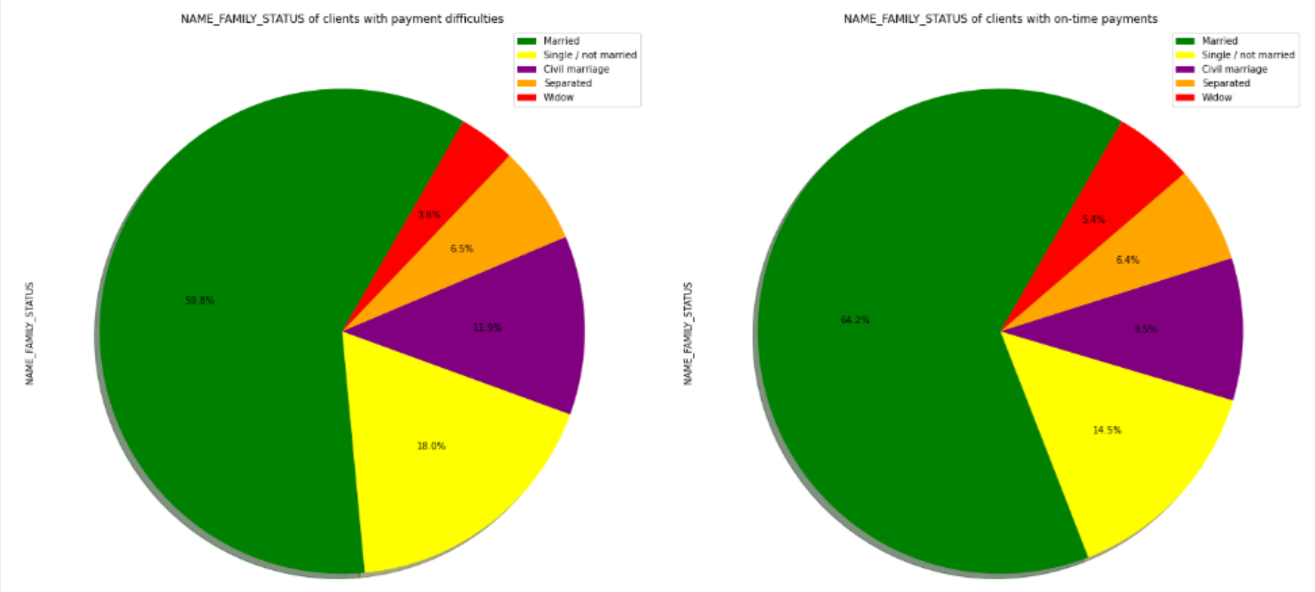
Analysis of \`NAME_INCOME_TYPE\`

- \- Pensioners have better on-time payments. This is a weak correlation.
- \- Students don't have Payment difficulties. In this case, total students have only 18 observations and should be treated as a weak correlation
- \- Businessmen don't have Payment difficulties. In this case, Businessmen have only 10 observations and should be treated as a weak correlation



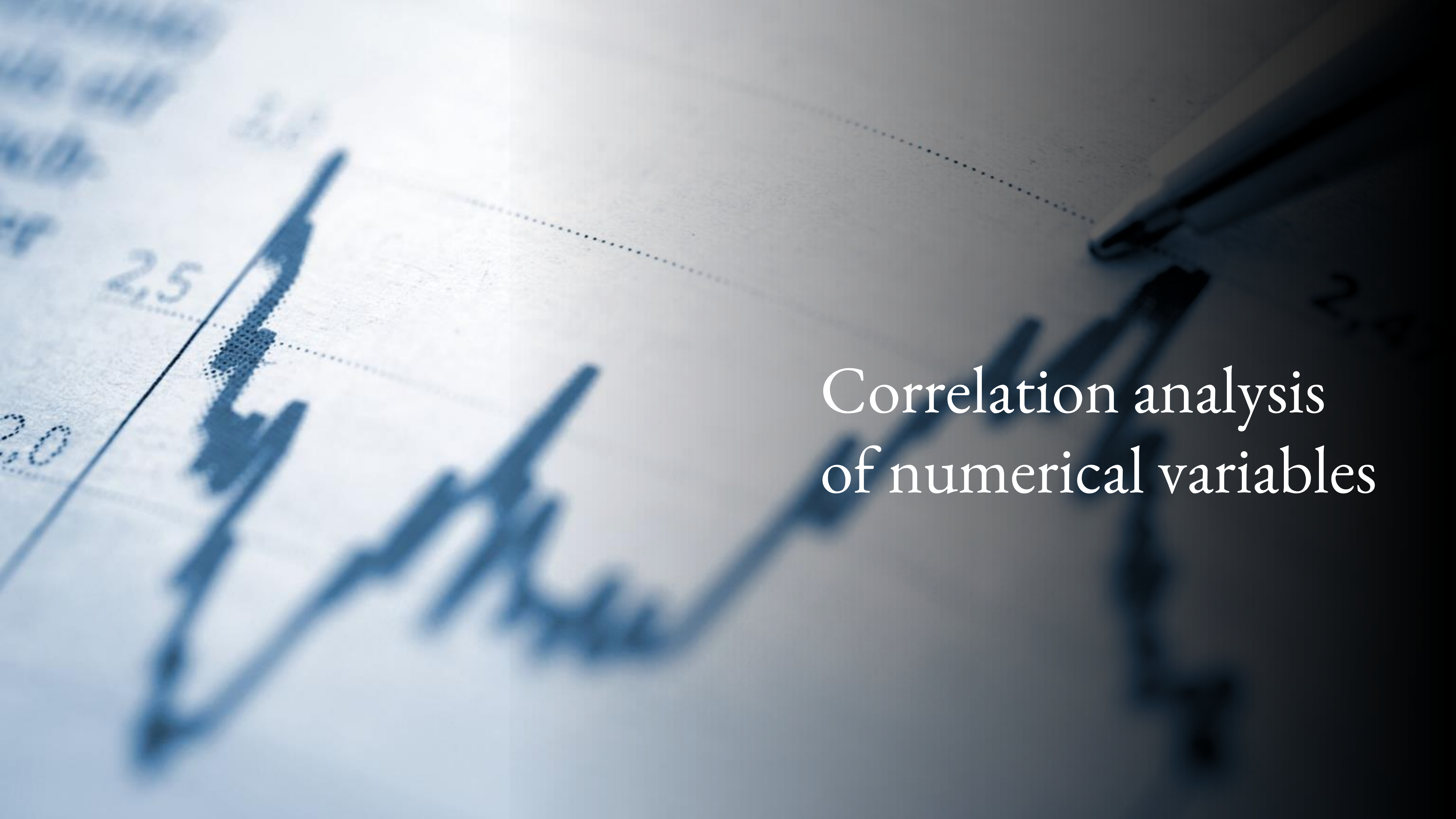
Analysis of `NAME_EDUCATION_TYPE`

- - Clients with 'Higher education' have less payment difficulties. However, this is a weak correlation



Analysis of `NAME_FAMILY_STATUS`

- - Clients who are 'Married' are 59.8% with payment difficulties and 64.2% with on-timepayments
- - Clients who are 'Widow' are 3.8% with payment difficulties and 5.4% with on-timepayments
- - Clients who are 'Single/not married' are 18.0% with payment difficulties and 14.5% with on-timepayments
- - Clients who are 'Married' OR 'Widow' do on-time payments better comparatively. However, this is a weak correlation.
- - Clients who are 'Single/not married' have more difficulties with on-time payments comparatively. However, this is a weak correlation.



Correlation analysis of numerical variables

- AMT_GOODS_PRICE AMT_CREDIT 0.98
- REGION_RATING_CLIENT REGION_RATING_CLIENT_W_CITY 0.96
- CNT_FAM_MEMBERS CNT_CHILDREN 0.89
- DEF_60_CNT_SOCIAL_CIRCLE DEF_30_CNT_SOCIAL_CIRCLE 0.87
- REG_REGION_NOT_WORK_REGION LIVE_REGION_NOT_WORK_REGION 0.85
- LIVE_CITY_NOT_WORK_CITY REG_CITY_NOT_WORK_CITY 0.78
- AMT_ANNUITY AMT_GOODS_PRICE 0.75
- AMT_ANNUITY AMT_CREDIT 0.75
- DAYS_EMPLOYED FLAG_DOCUMENT_6 0.62
- DAYS_BIRTH DAYS_EMPLOYED 0.58

With Payment difficulties

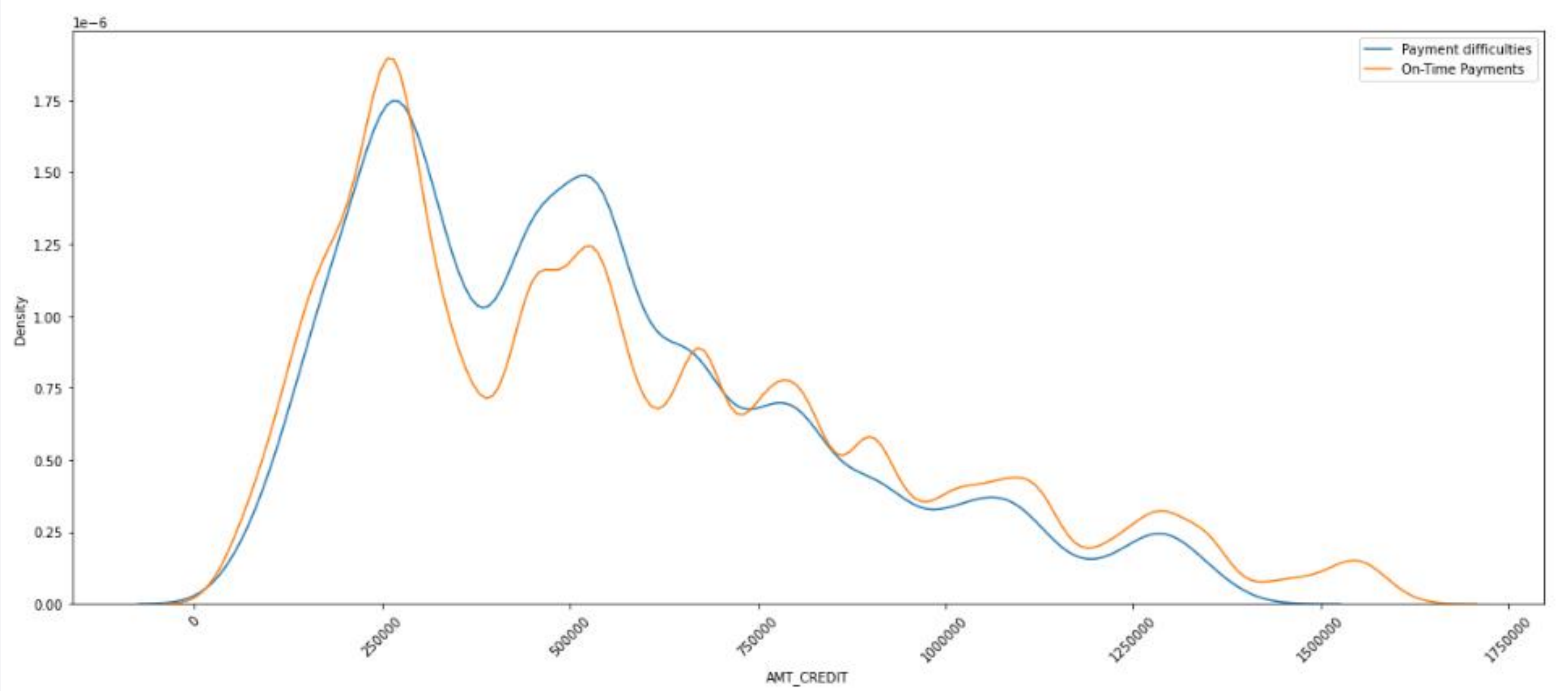
- Getting top 10 correlations

- AMT_GOODS_PRICE AMT_CREDIT 0.99
- REGION_RATING_CLIENT REGION_RATING_CLIENT_W_CITY 0.95
- CNT_FAM_MEMBERS CNT_CHILDREN 0.88
- REG_REGION_NOT_WORK_REGION LIVE_REGION_NOT_WORK_REGION 0.86
- DEF_30_CNT_SOCIAL_CIRCLE DEF_60_CNT_SOCIAL_CIRCLE 0.86
- LIVE_CITY_NOT_WORK_CITY REG_CITY_NOT_WORK_CITY 0.83
- AMT_ANNUITY AMT_GOODS_PRICE 0.78
- AMT_ANNUITY AMT_CREDIT 0.77
- DAYS_BIRTH DAYS_EMPLOYED 0.63
- DAYS_EMPLOYED FLAG_DOCUMENT_6 0.60

On-Time payments

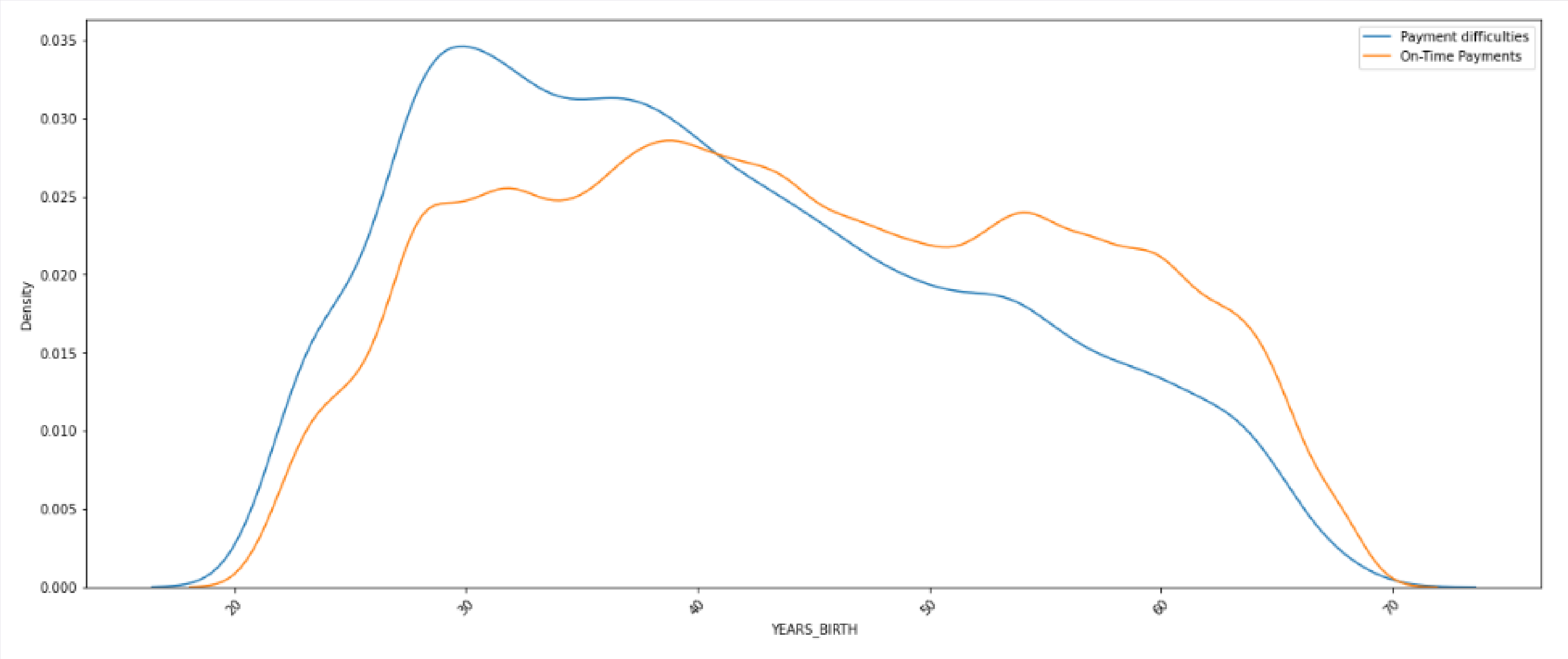
- Getting top 10 correlations

Univariate analysis of numerical variables



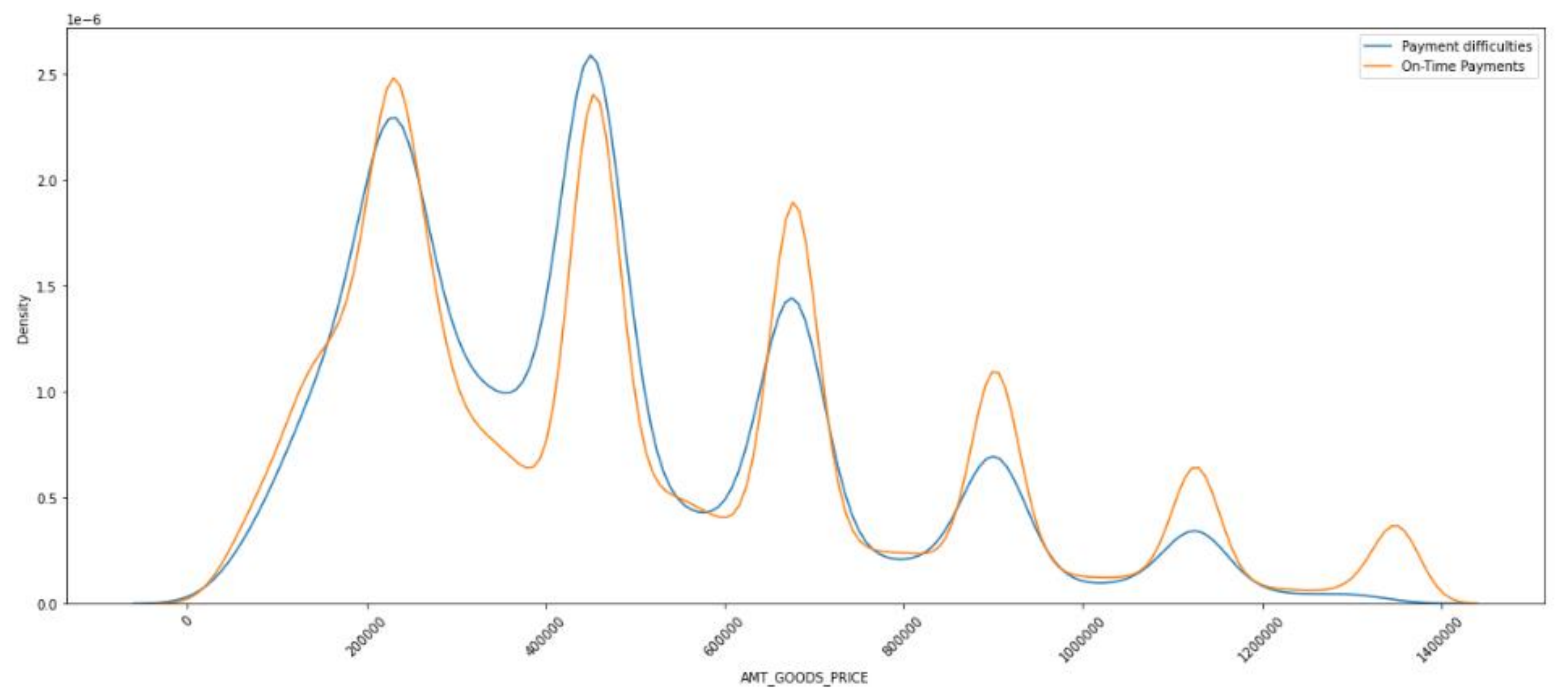
Analysis of \`AMT_CREDIT\`

- \- For \`AMT_CREDIT\` between 250000 and approximately 650000, there are more clients with Payment difficulties
- \- For \`AMT_CREDIT\` > 750000 , there are more clients with On-Time Payments



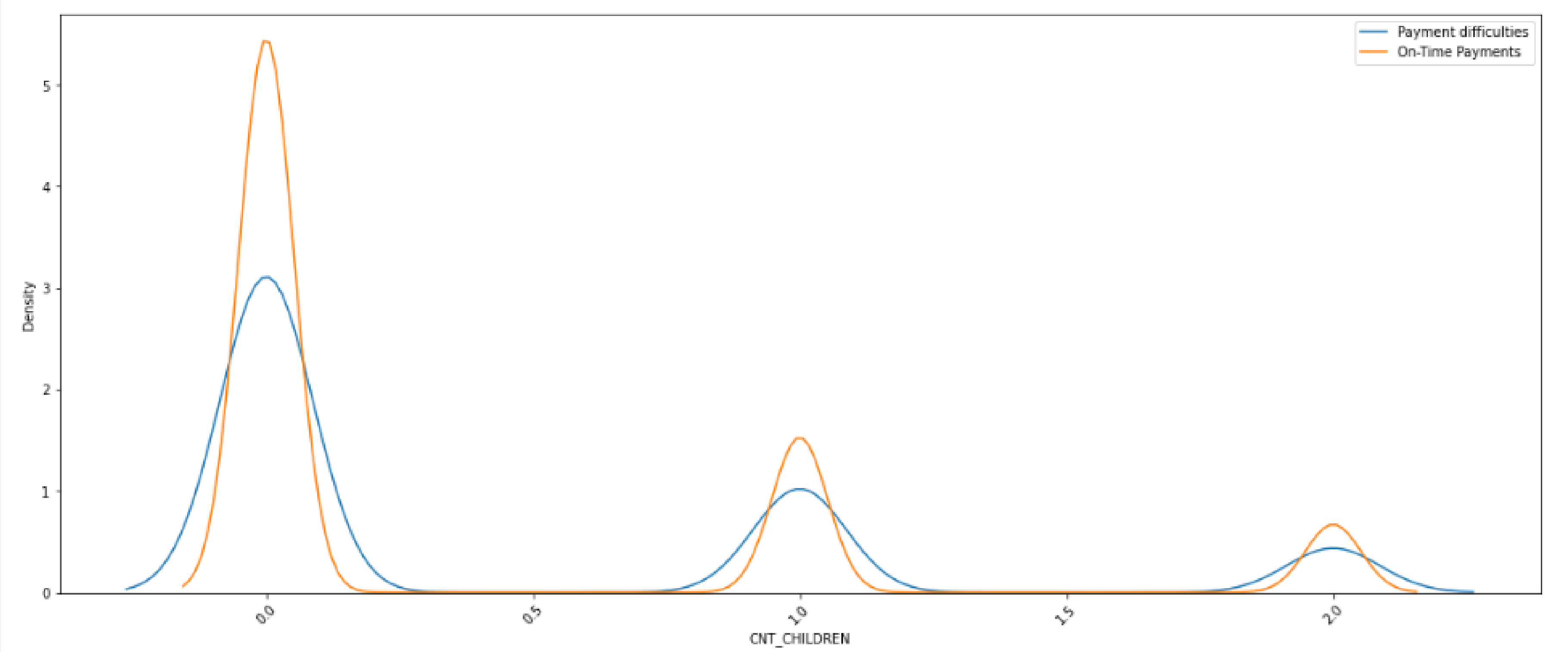
Analysis of `YEARS_BIRTH`

- \- For `YEARS_BIRTH` between 20 and 40, there are more clients with Payment difficulties
- \- Conversely, for `YEARS_BIRTH` > 40 , there are more clients with On-Time Payments



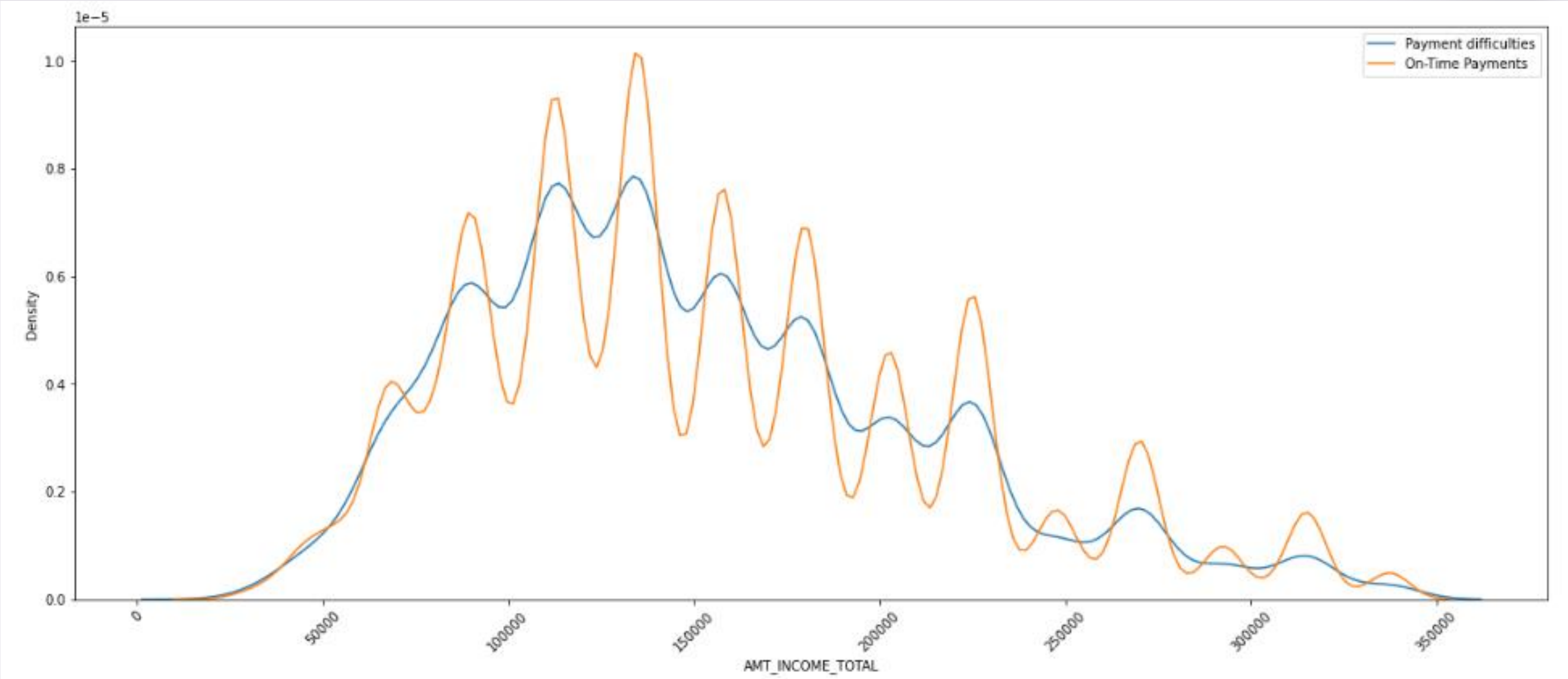
Analysis of \`AMT_GOODS_PRICE\`

- \- For \`AMT_GOODS_PRICE\` between ~250000 and ~550000, there are more clients with Payment difficulties
- \- Otherwise there are spikes on and off but they don't show any conclusive observations



Analysis of `CNT_CHILDREN`

- - For `CNT_CHILDREN` 0 (those with no children), there are lots of clients with On-Time Payments
- - For `CNT_CHILDREN` with 1 OR 2 (those with 1 or 2 children), there are few more clients with On-Time Payments

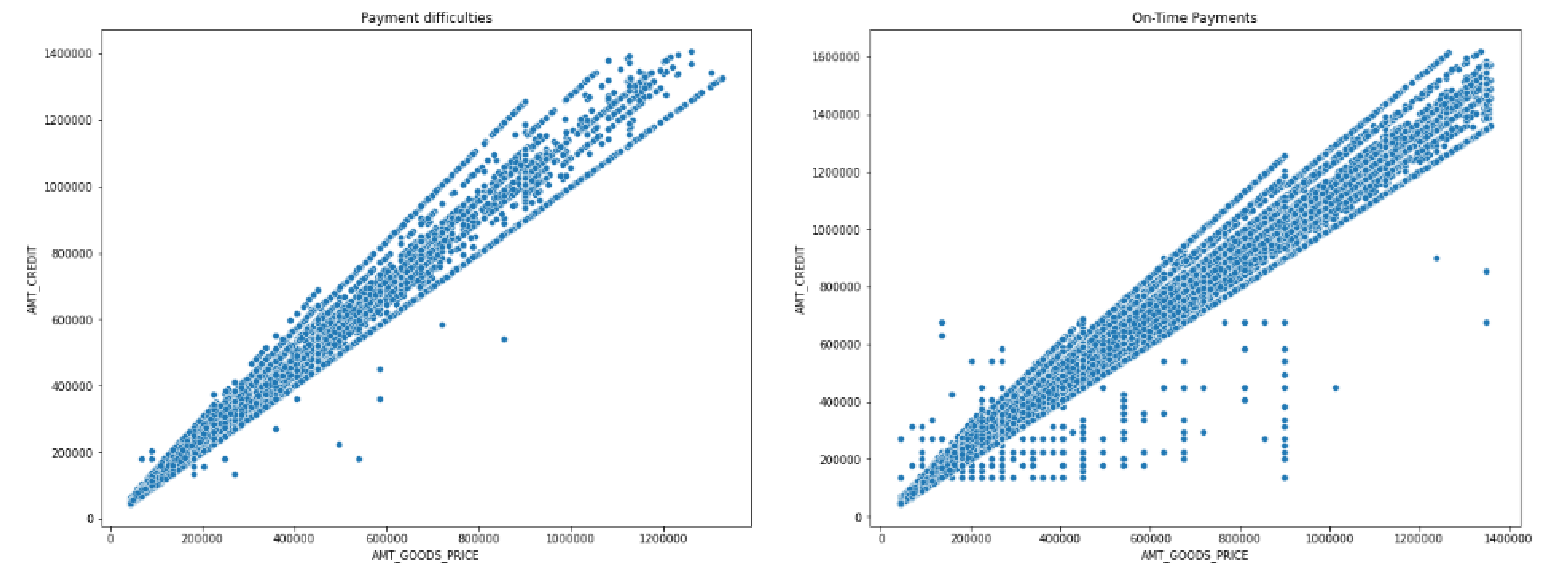


Analysis of `AMT_INCOME_TOTAL`

- - Based on `AMT_INCOME_TOTAL`, for clients with Payment difficulties, the distribution resembles a normal distribution approximately
- - But for clients with On-Time Payments, there are erratic spikes in the distribution which doesn't give any valid observations

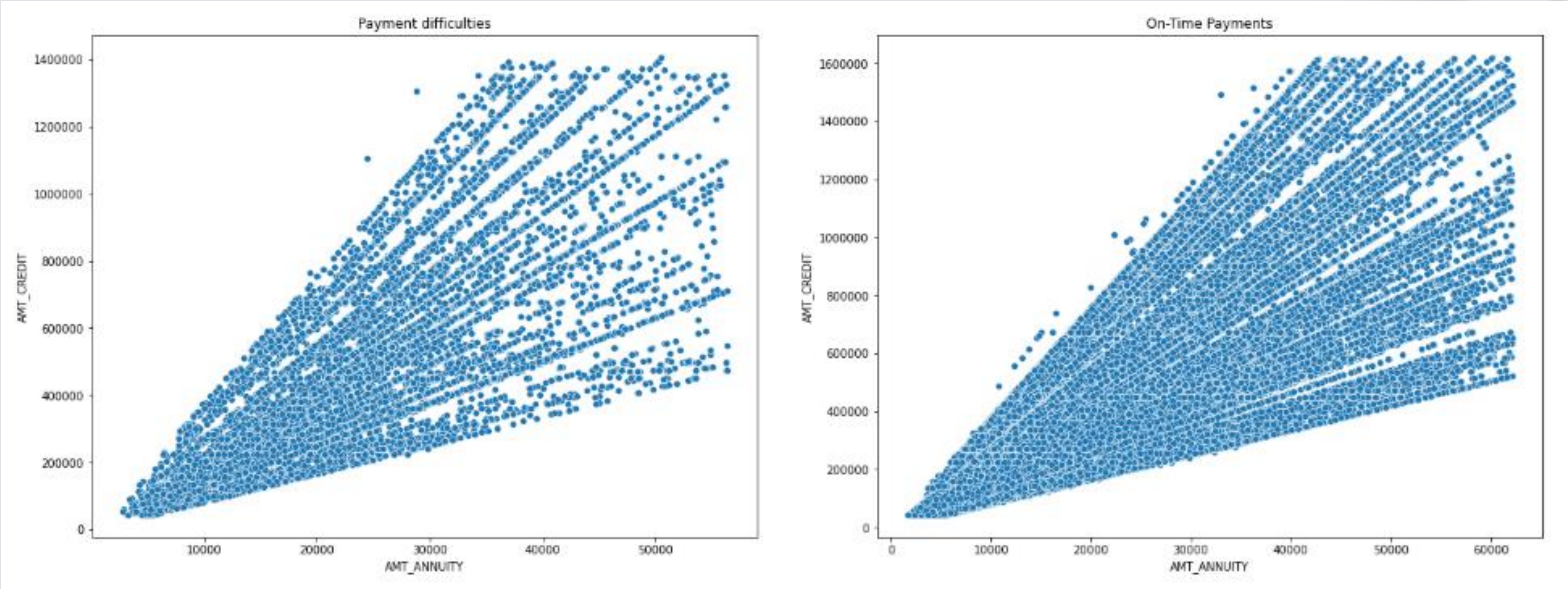
Bivariate/Multivariate analysis

Continuous V/S Continuous variables



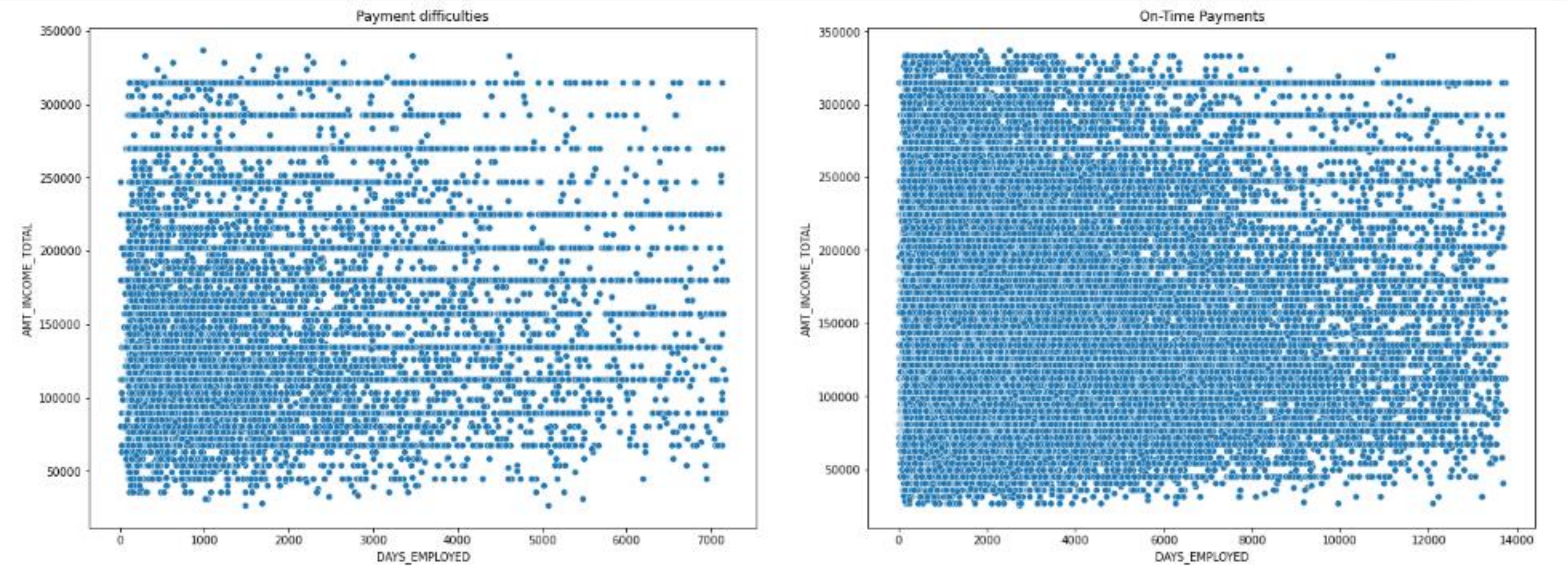
Analysis of `AMT_GOODS_PRICE` V/S `AMT_CREDIT

- - `AMT_GOODS_PRICE` and `AMT_CREDIT` have strong positive correlation. This means that as Goods price increases, so does Credit Amount



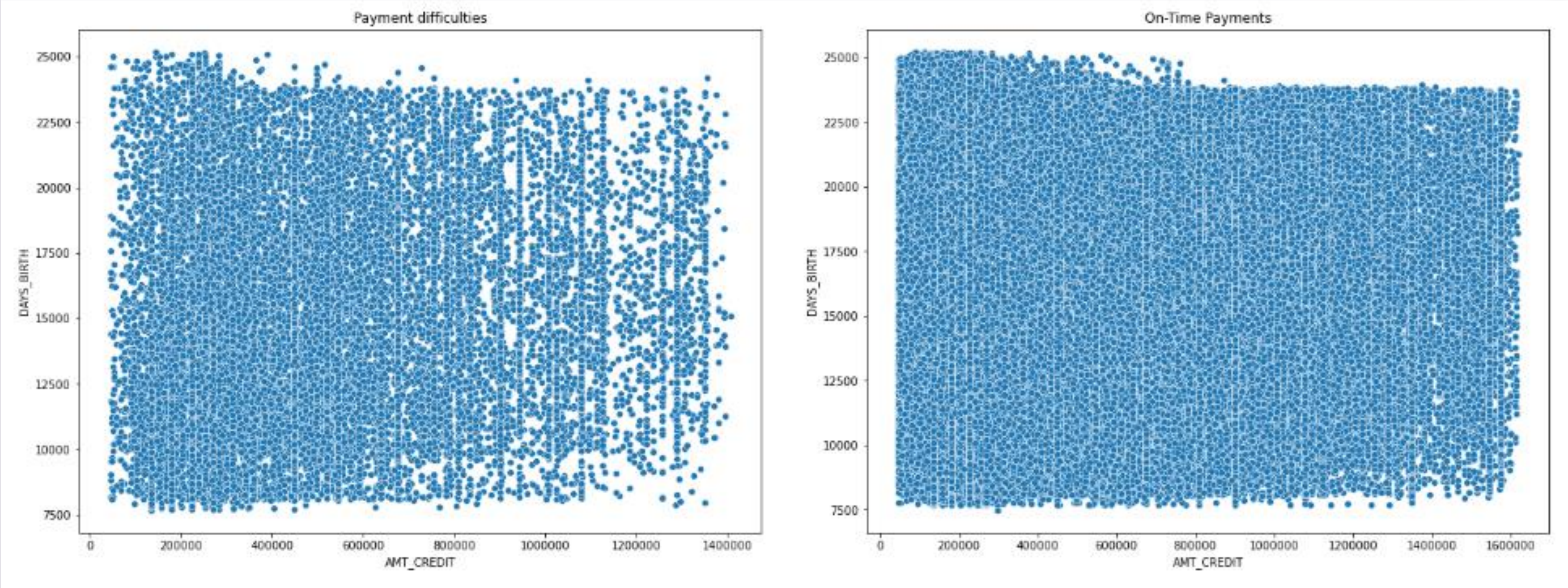
Analysis of `AMT_ANNUITY` V/S `AMT_CREDIT`

- - `AMT_ANNUITY` and `AMT_CREDIT` have strong positive correlation. This means that as Annuity Amount increases, so does Credit Amount



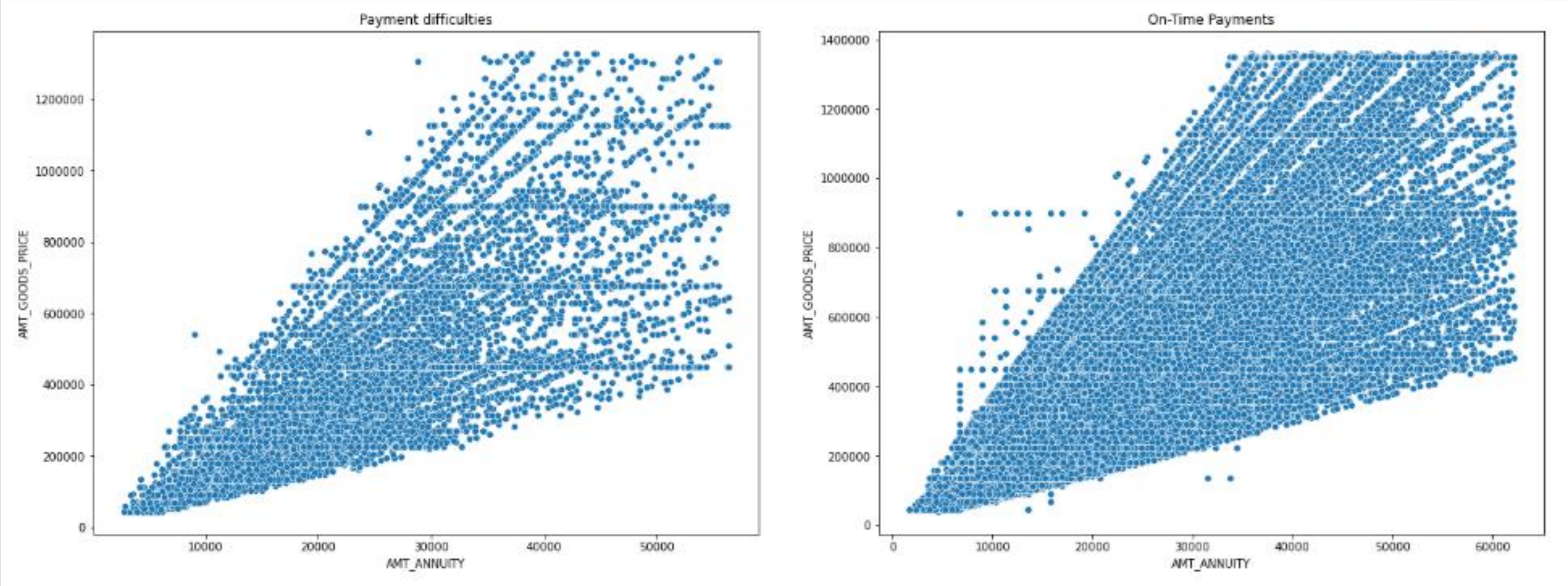
Analysis of `DAYS_EMPLOYED` V/S `AMT_INCOME_TOTAL`

- - Clients who are employed for a long time (>7000) days or 19 years are making their payments on-time but these category of clients do not exist in Payments difficulties group
- - Even looking at Payment difficulties group, clients with more than 4000 days of employment are sparse



Analysis of `AMT_CREDIT` V/S `DAYS_BIRTH`

- - There is no observable correlation between Days of Birth and Amount of Credit

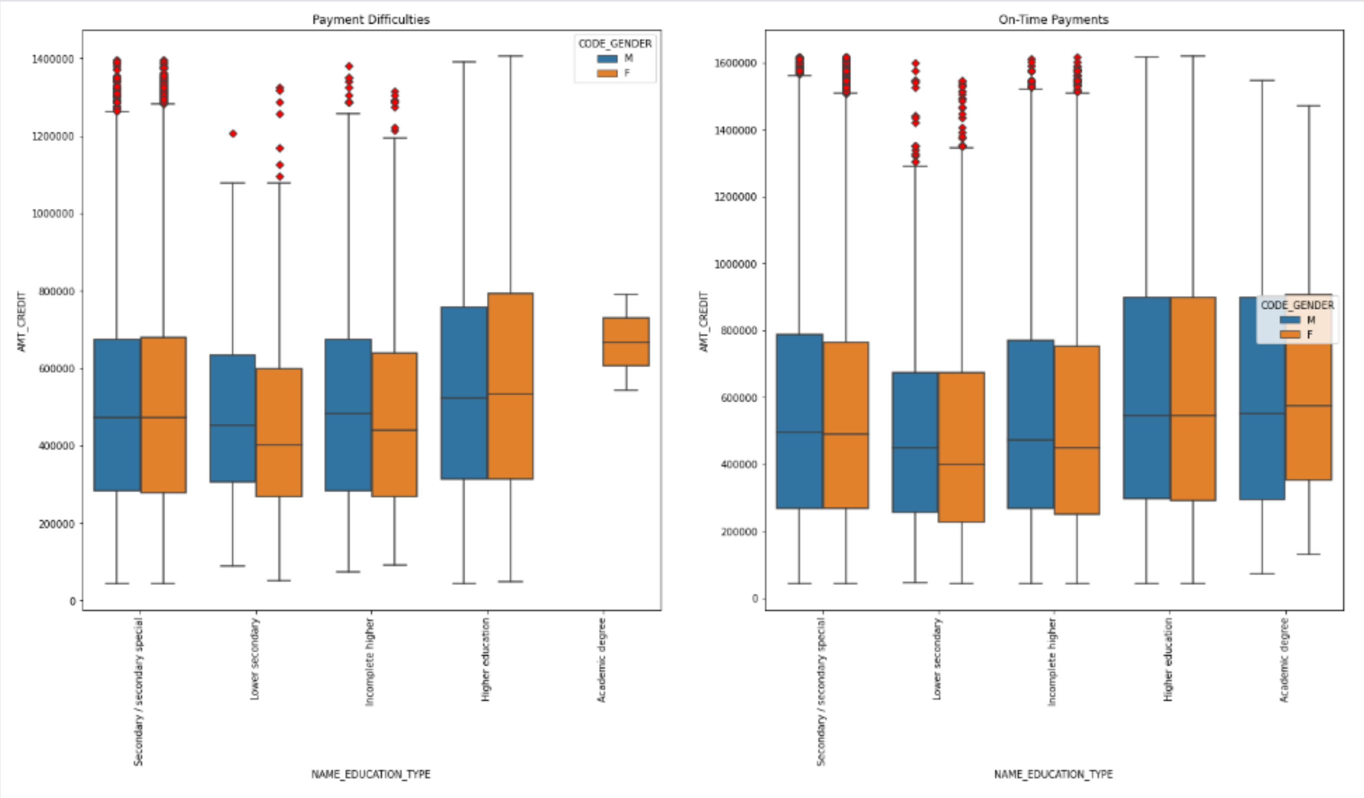


Analysis of `AMT_ANNUITY` V/S `AMT_GOODS_PRICE`

- - `AMT_ANNUITY` and `AMT_GOODS_PRICE` have strong positive correlation. This means that as Annuity increases, so does Goods Price

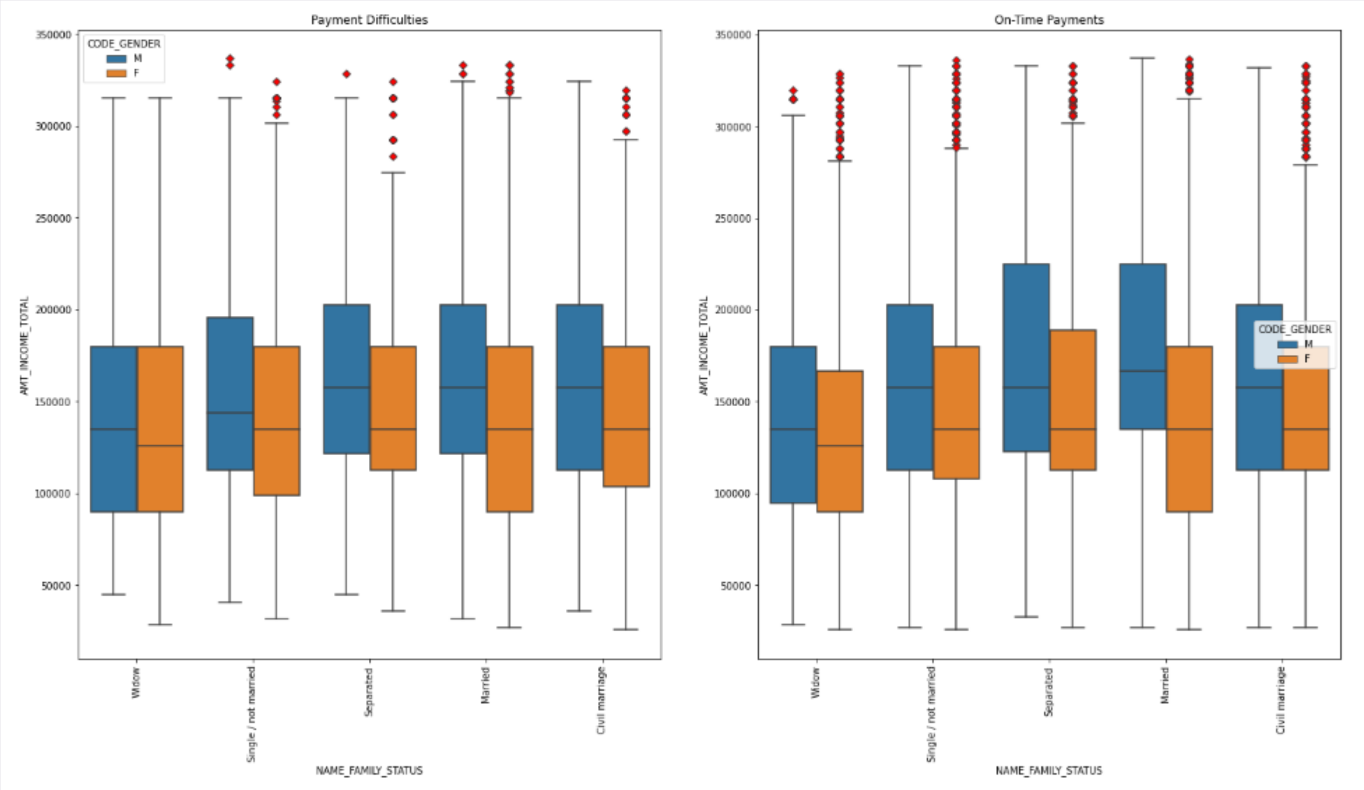
Bivariate/Multivariate analysis

Continuous V/S Categorical variables



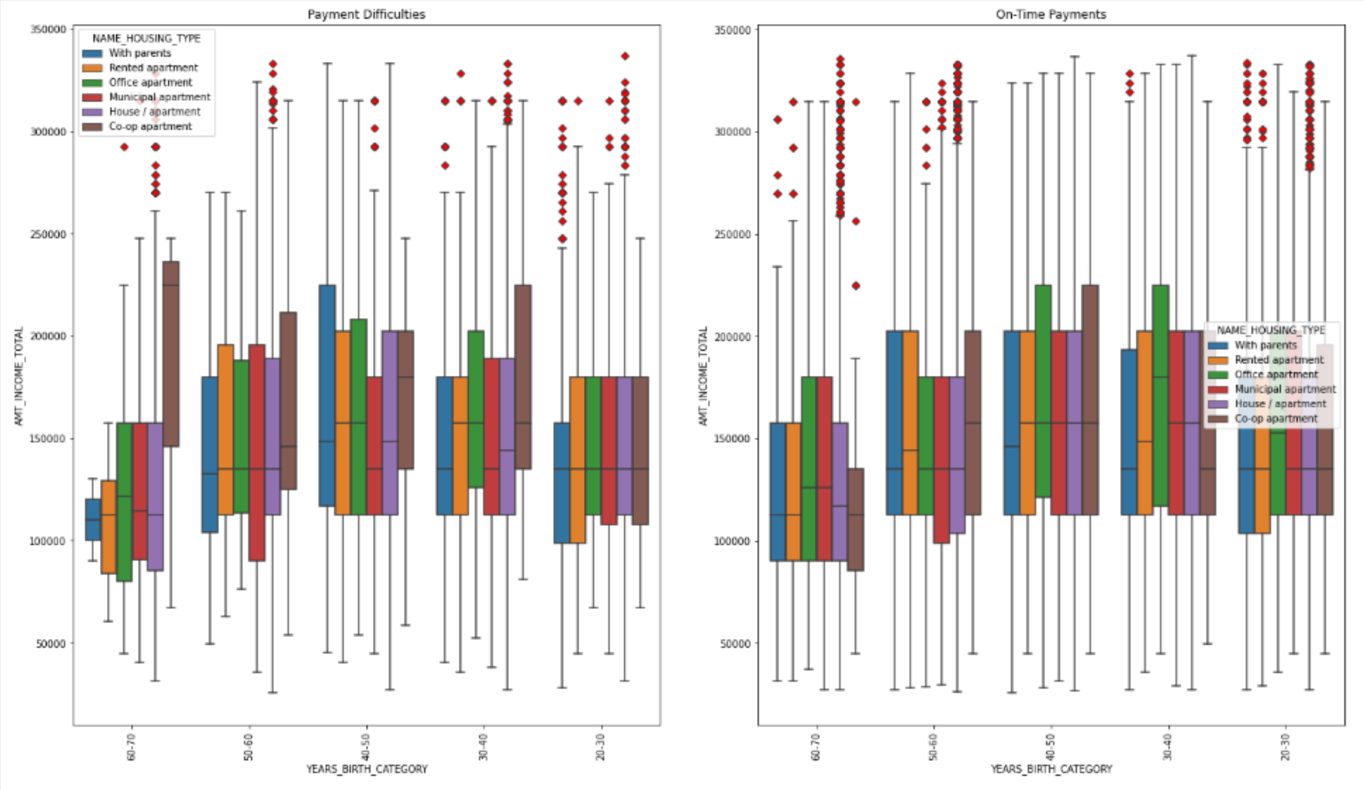
Analysis of `NAME_EDUCATION_TYPE` V/S `AMT_CREDIT` V/S `CODE_GENDER`

- - Clients with `Academic Degree` have a wide range of credits for On-Time Payments whereas the range is much lower for ones with Payment difficulties
- - Looking at summary statistics, Clients with `Academic Degree` and Payment difficulties take mean and median credit at a much higher range than On-Time Payment clients
- - `Male` clients with `Academic Degree` always pay the loan on-time



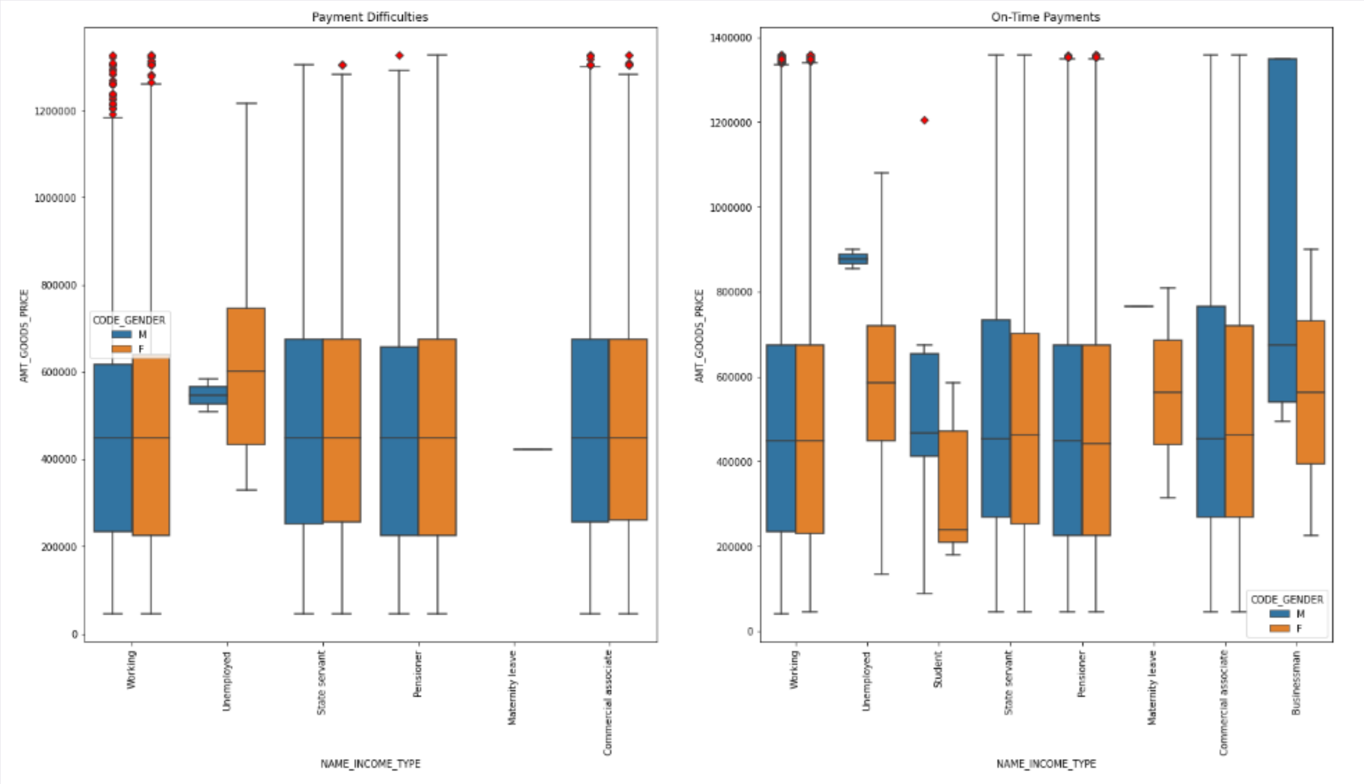
Analysis of `NAME_FAMILY_STATUS` V/S `AMT_INCOME_TOTAL` V/S `CODE_GENDER`

- - `Married` clients have a slightly higher mean/median income with On-Time Payments than Payment difficulties category



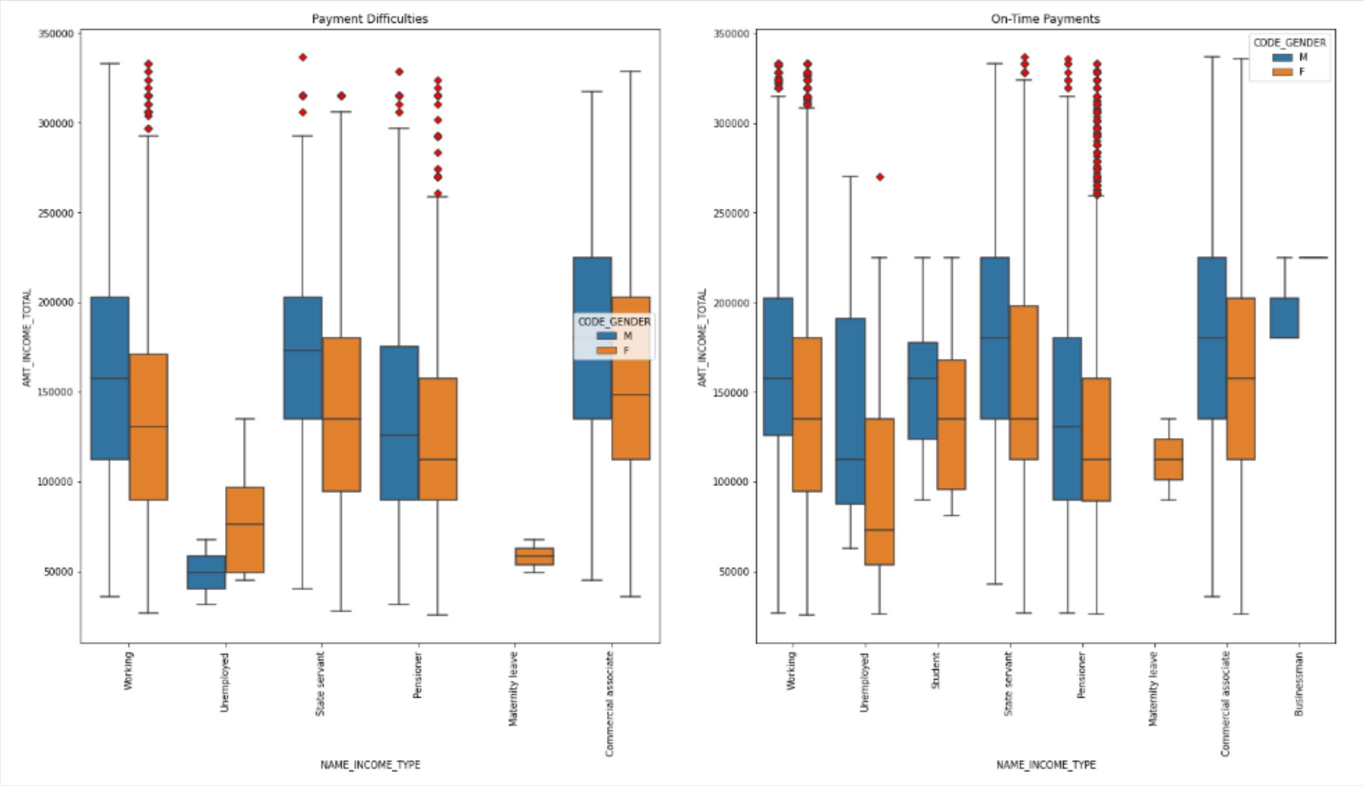
Analysis of `YEARS_BIRTH_CATEGORY` V/S `AMT_INCOME_TOTAL` V/S `NAME_HOUSING_TYPE`

- - Clients with age `60-70` and living in `Co-op apartment` have very high-income range in Payment difficulties category than On-Time Payments
- - Clients with age `20-30` and living in `Office apartment` have very higher income median in On-Time Payments compared to Payment difficulties category



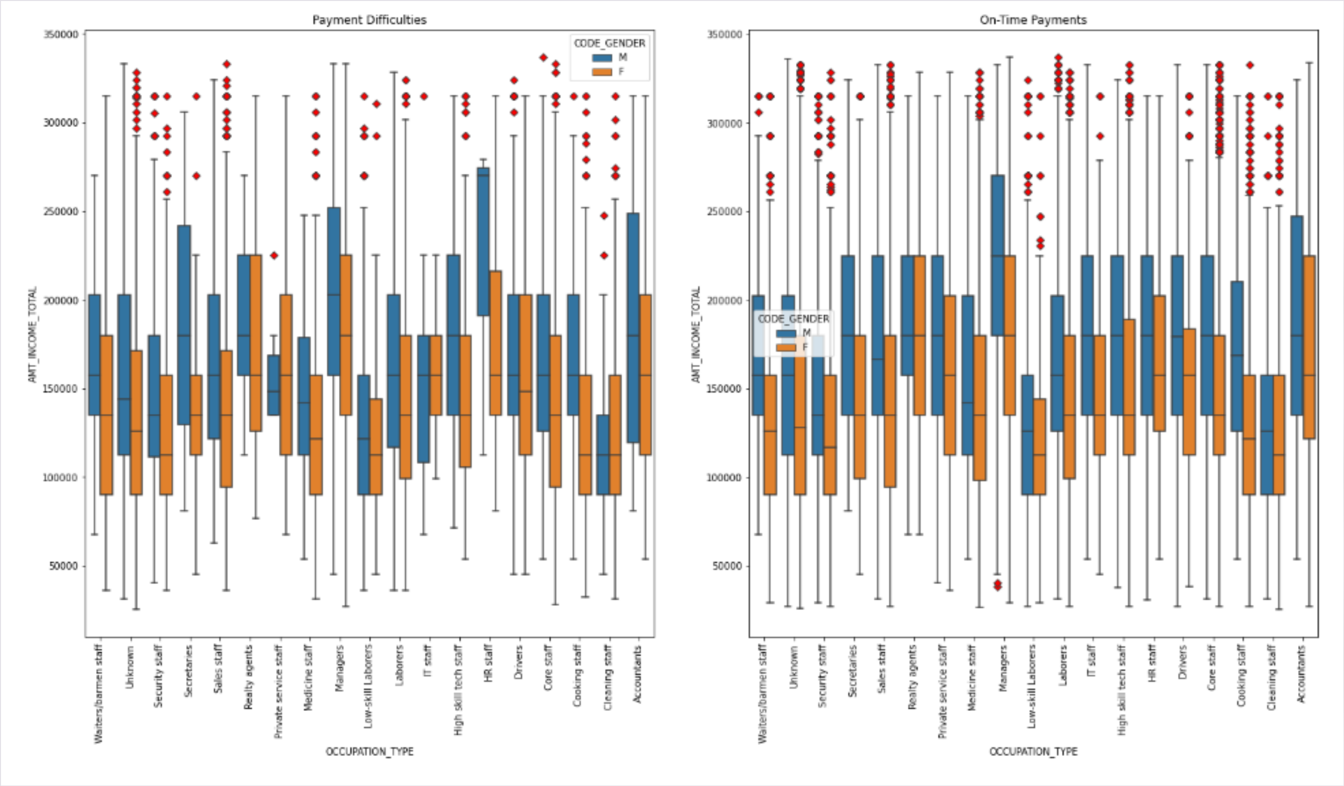
Analysis of \`NAME_INCOME_TYPE\` V/S \`AMT_GOODS_PRICE\` V/S \`CODE_GENDER\`

- \- Clients who are \`Unemployed\` and \`Male\` have a very high price of goods in On-Time Payments than Payment difficulties
- \- Clients who are \`Student\` and either \`Male\` OR \`Female\` do their payments On-Time. They are completely missing from Payment difficulties category. \`Student\` seems to be an attractive category to give loans to.
- \- Clients who are \`Businessman\` and either \`Male\` OR \`Female\` do their payments On-Time. They are completely missing from Payment difficulties category. \`Businessman\` seems to be an attractive category to give loans to.



Analysis of `NAME_INCOME_TYPE` V/S `AMT_INCOME_TOTAL` V/S `CODE_GENDER`

- \- Clients who are `Unemployed` and `Male` have a very high income in On-Time Payments than Payment difficulties
- \- Clients who are `Student` and either `Male` OR `Female` do their payments On-Time. They are completely missing from Payment difficulties category. `Student` seems to be an attractive category to give loans to.
- \- Clients who are `Businessman` and either `Male` OR `Female` do their payments On-Time. They are completely missing from Payment difficulties category. `Businessman` seems to be an attractive category to give loans to.
- \- Clients who are in `Maternity Leave` and `Female` have a very high income in On-Time Payments than Payment difficulties

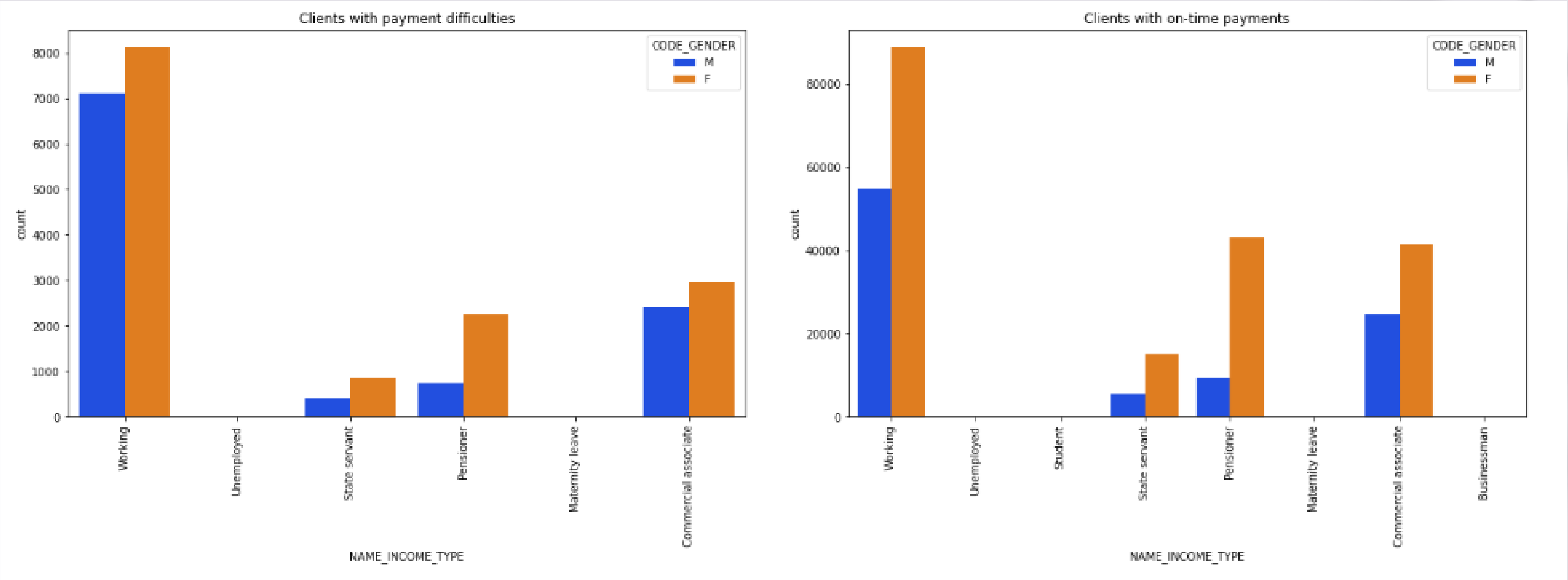


Analysis of \`OCCUPATION_TYPE\` V/S \`AMT_INCOME_TOTAL\` V/S \`CODE_GENDER\`

- - Clients who are \`Waiters/barment staff\` and \`female\` have less median income in On-Time Payments than Payment difficulties
- - Clients who are \`Cleaning staff\` and \`female\` have more median income in On-Time Payments than Payment difficulties
- - Clients who are \`HR Staff\` and \`Male\` have more median income in Payment difficulties than On-Time Payments
- - Clients who are \`Managers\` and \`Male\` have more median income in On-Time Payments than Payment difficulties

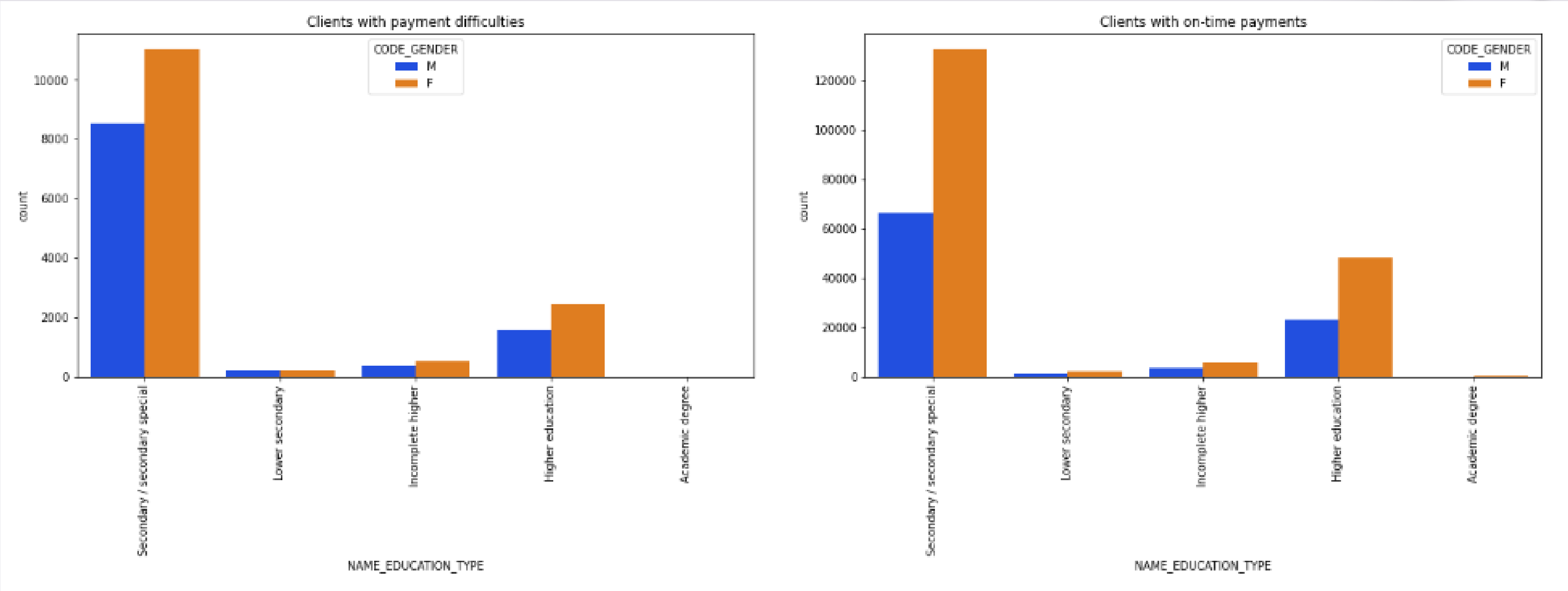
Bivariate/Multivariate analysis

Categorical V/S Categorical variables



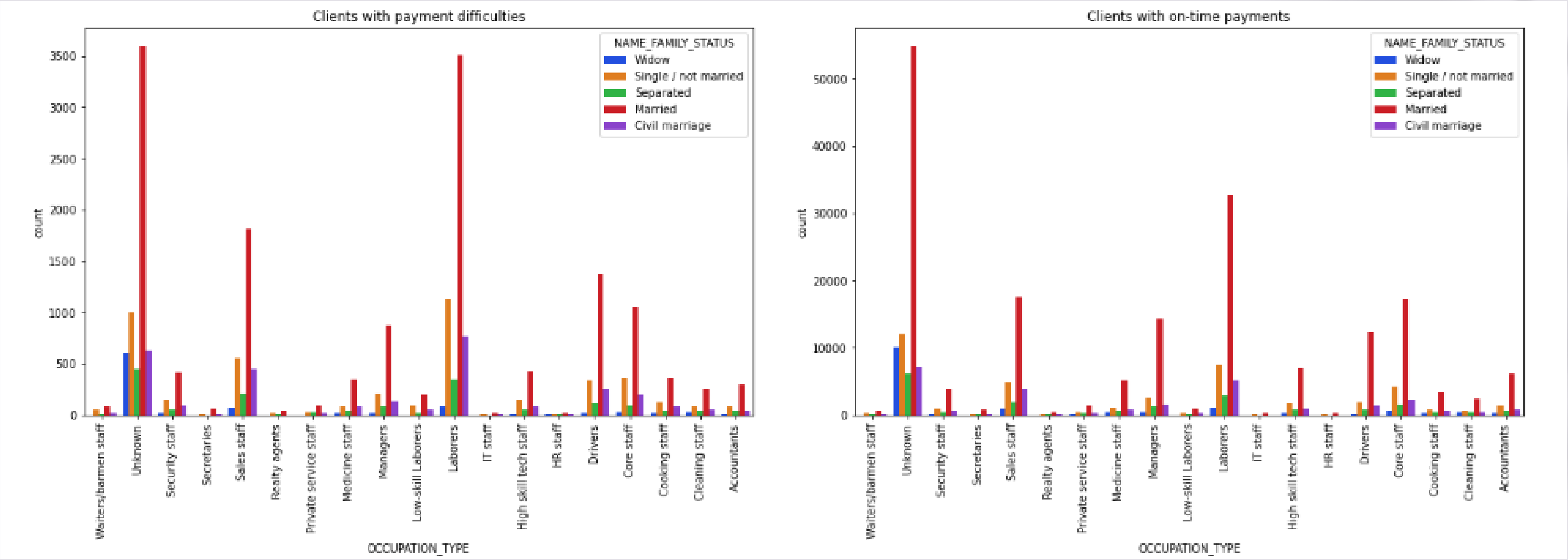
Analysis of `NAME_INCOME_TYPE` V/S `CODE_GENDER`

- - Clients who are `Working` and `Male` have more Payment difficulties compared to On-Time Payments
- - Clients who are `Pensioner` and `Female` have more Payment difficulties compared to On-Time Payments
- - Clients who are `Businessman` and `Students` do their payments On-Time though their record count is low



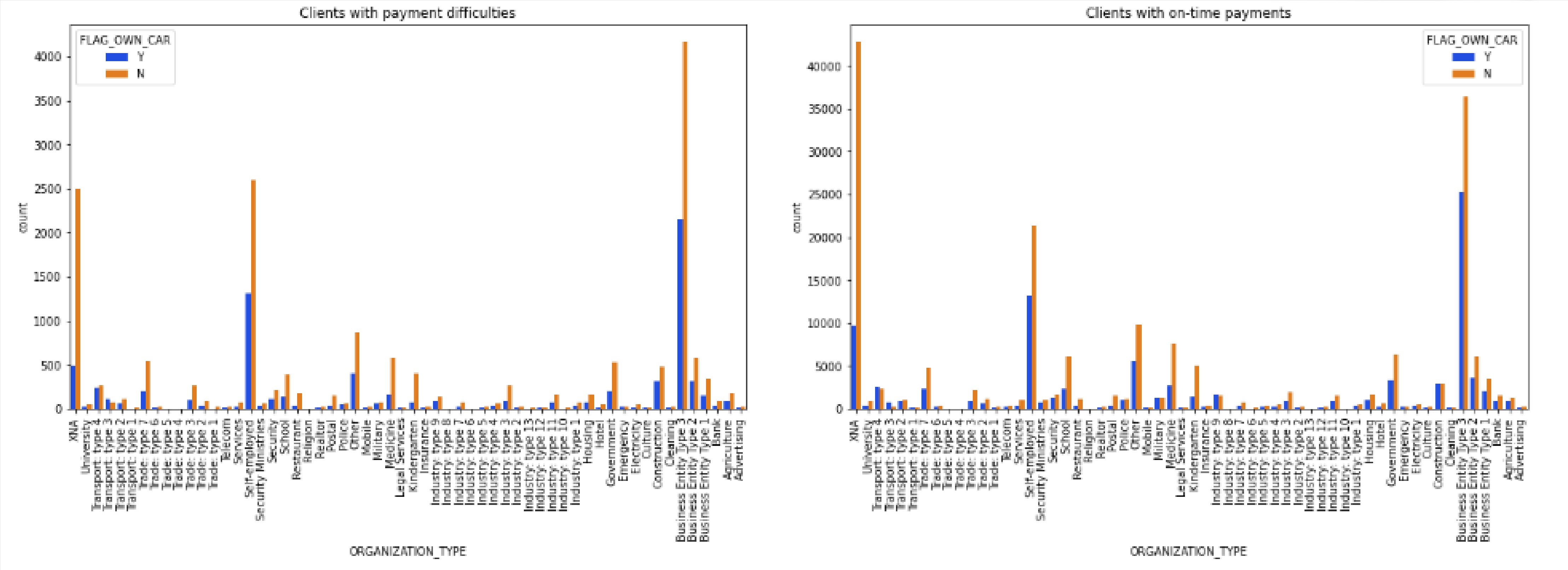
Analysis of `NAME_EDUCATION_TYPE` V/S `CODE_GENDER`

- - Clients who have `Secondary/Secondary special` education and `Male` have more Payment difficulties compared to On-Time Payments
- - Clients who have `Higher education` and `Female` have more On-Time Payments compared to Payment difficulties



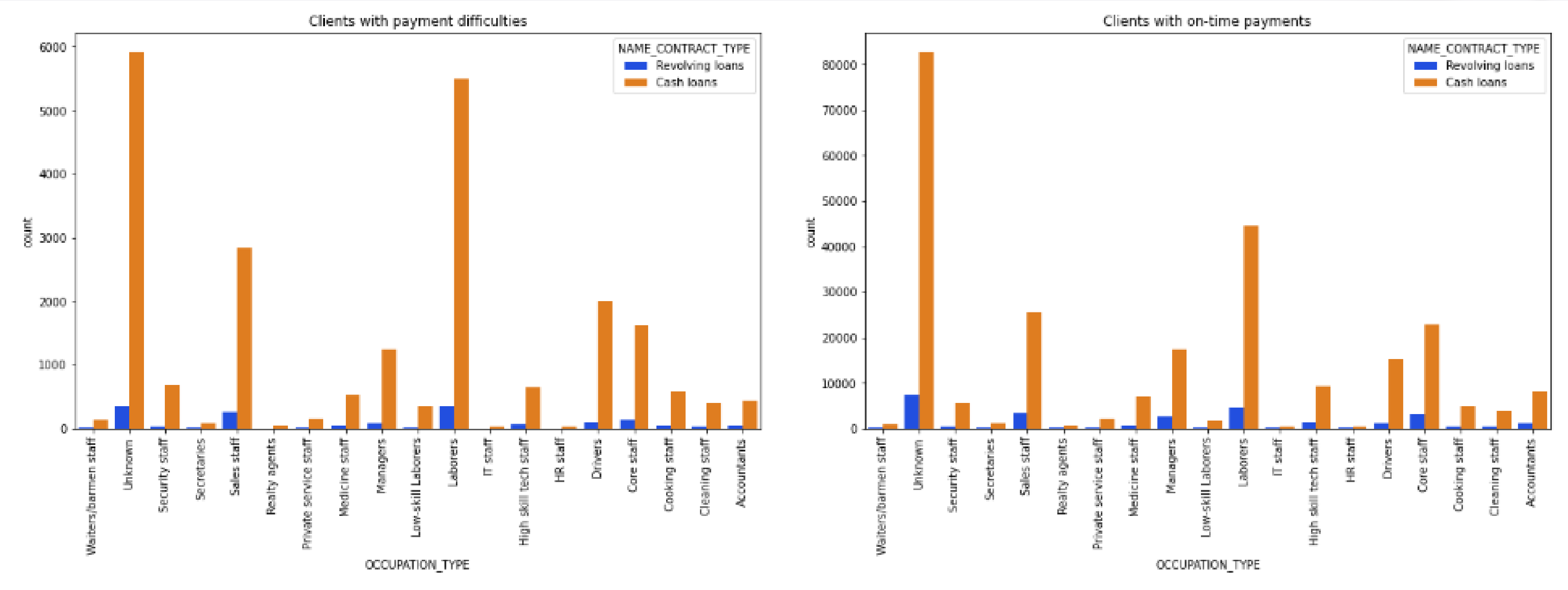
Analysis of \`NAME_FAMILY_STATUS\` V/S \`OCCUPATION_TYPE\`

- \- Clients who are \`Single/not married\`, \`Married\` & \`Civil marriage\` and are \`Waiters/barmen staff\` have more Payment difficulties compared to On-Time Payments
- \- Clients who are \`Single/not married\` & \`Married\` and are \`Laborers\` have more Payment difficulties compared to On-Time Payments
- \- Clients who are \`Married\` and are \`Drivers\` have more Payment difficulties compared to On-Time Payments
- \- \`Married\` and \`Accountants\` have better On-Time Payments



Analysis of \`ORGANIZATION_TYPE\` V/S \`FLAG_OWN_CAR\`

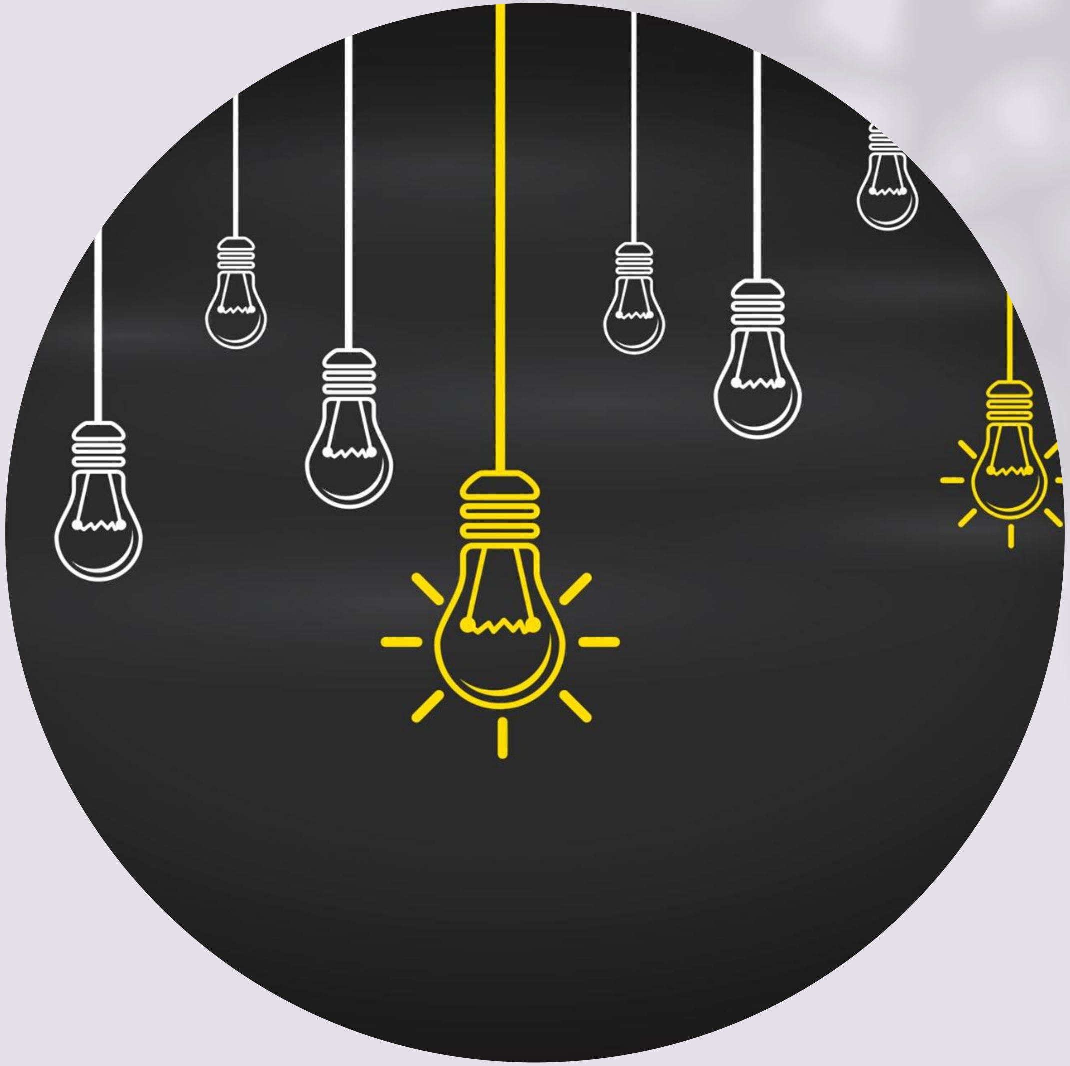
- \- Clients who are \`Self-employed\`and don't own \`Car\` have more Payment difficulties compared to On-Time Payments



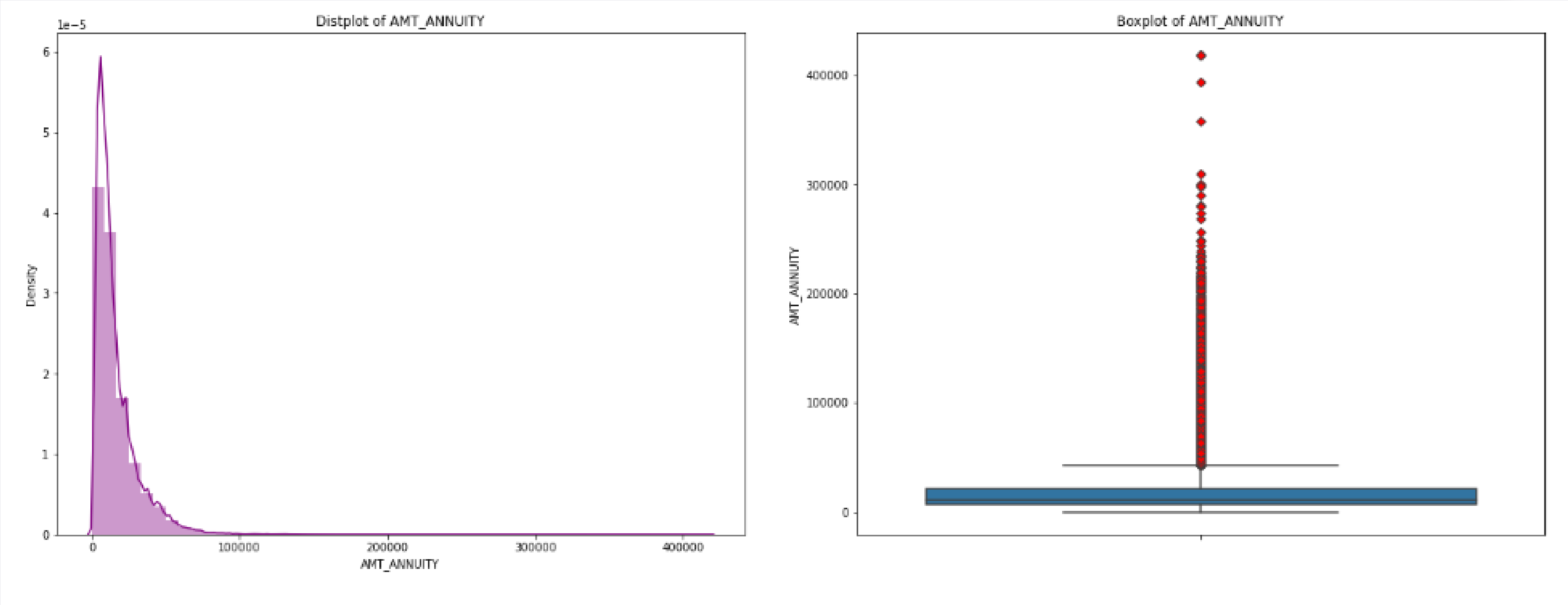
Analysis of `OCCUPATION_TYPE` V/S `NAME_CONTRACT_TYPE`

- - Clients who are `Sales staff`, `Laborers`, `Drivers` and have `Cash loans` have more Payment difficulties compared to On-Time Payments

Analysis of information about the client’s previous loan data

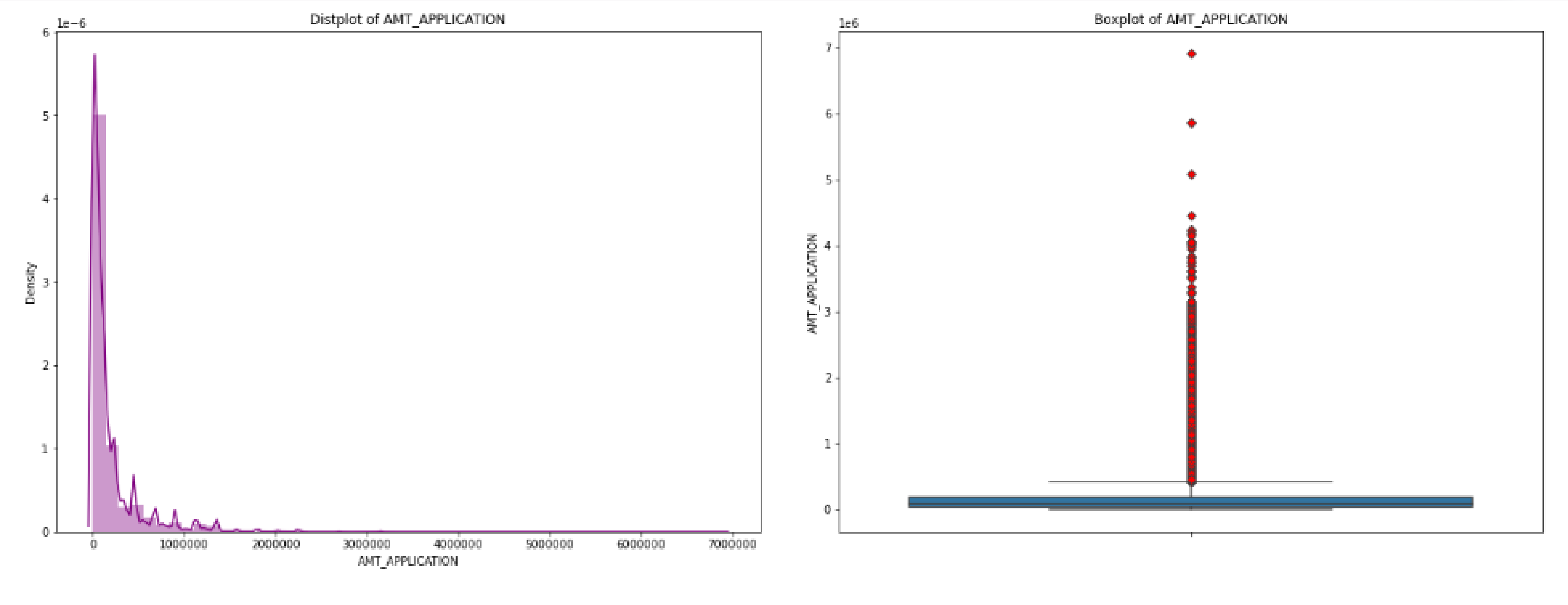


Outlier analysis



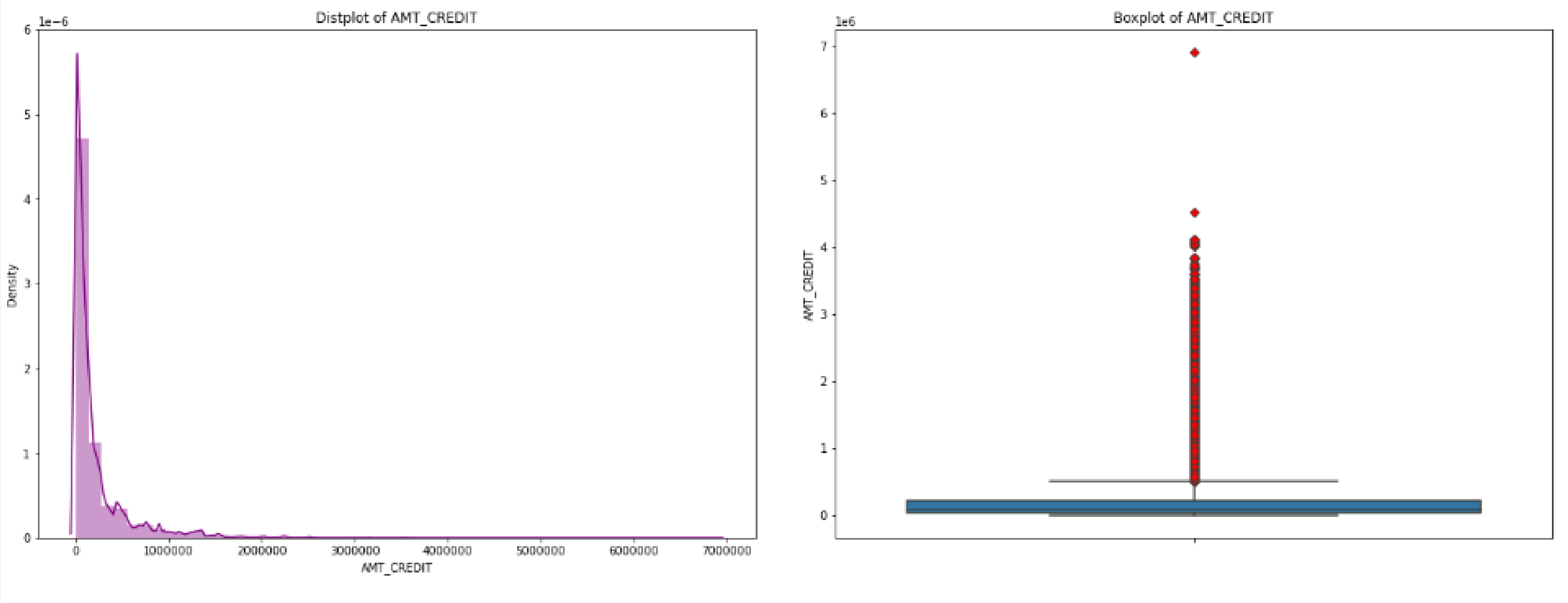
Analysis of \`AMT_ANNUITY\` column

- \- \`AMT_ANNUITY\` values above 42163.38 are outliers



Analysis of \`AMT_APPLICATION\` column

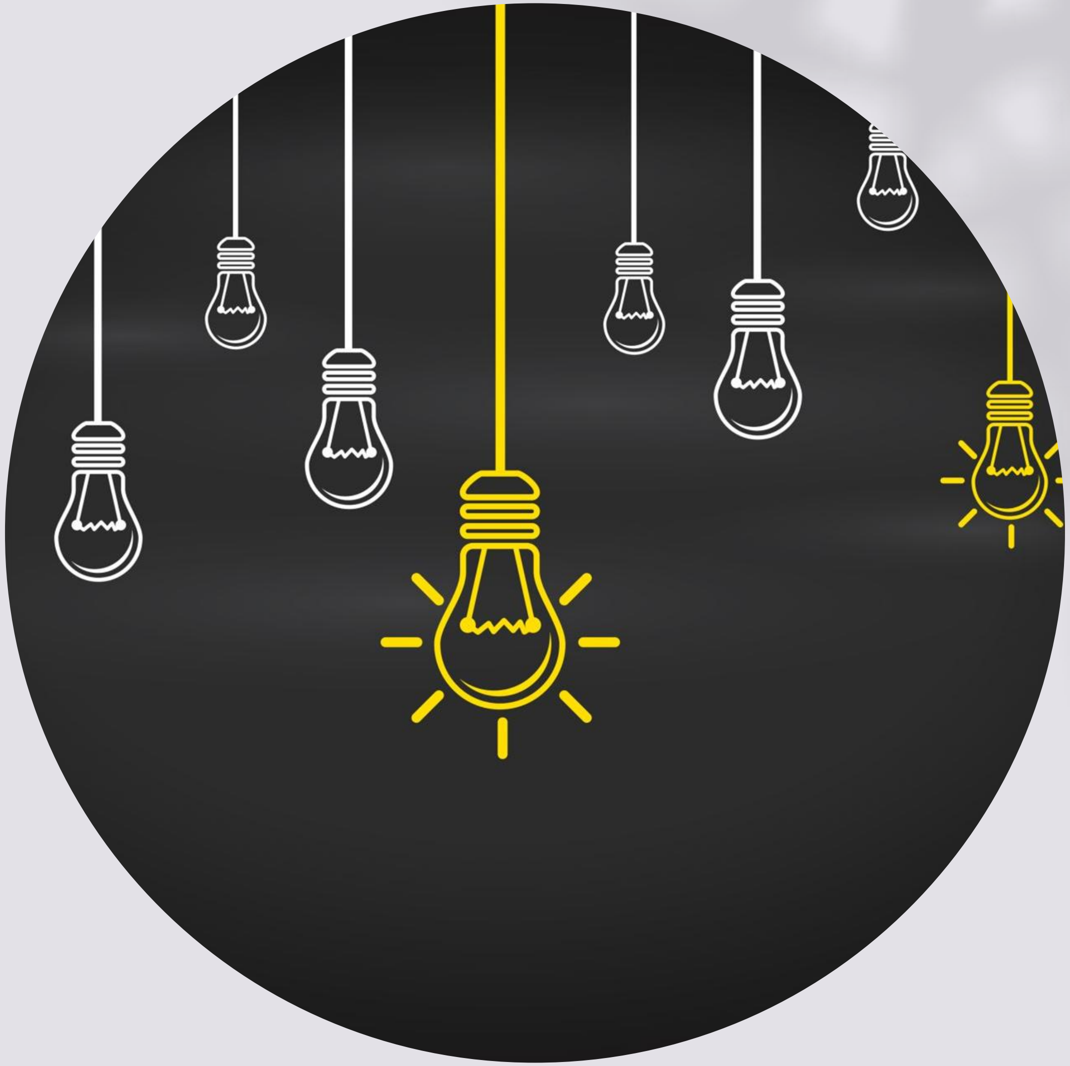
- \- \`AMT_APPLICATION\` values above 422820.0 are outliers



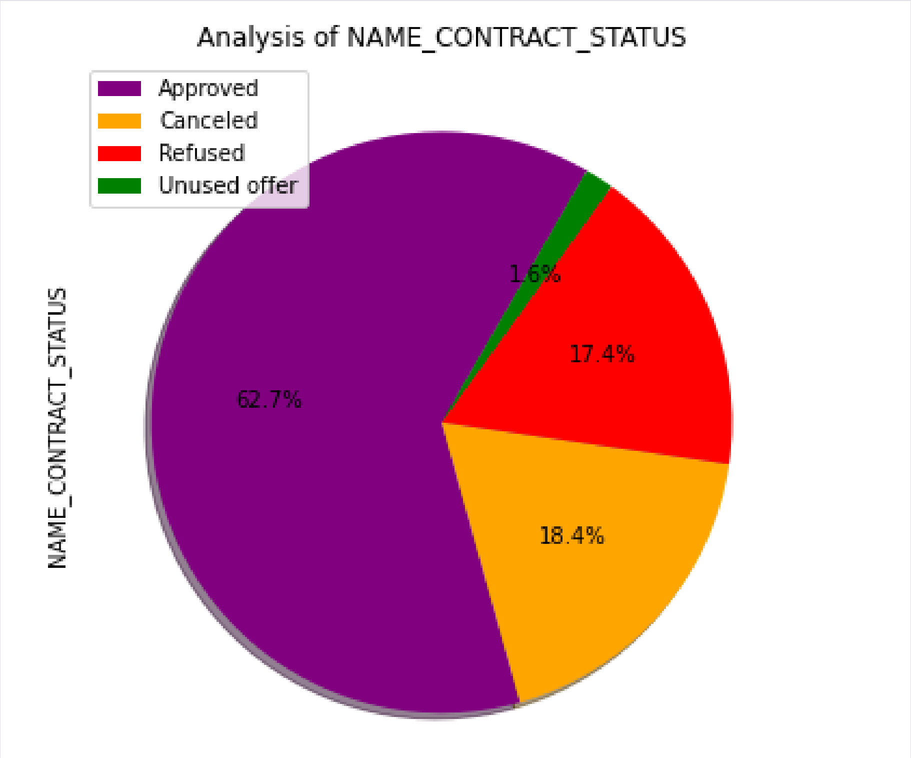
Analysis of `AMT_CREDIT` column

- \- `AMT_CREDIT` values above 504805.5 are outliers

Analysis of merged information about the client’s previous loan data and current loan application

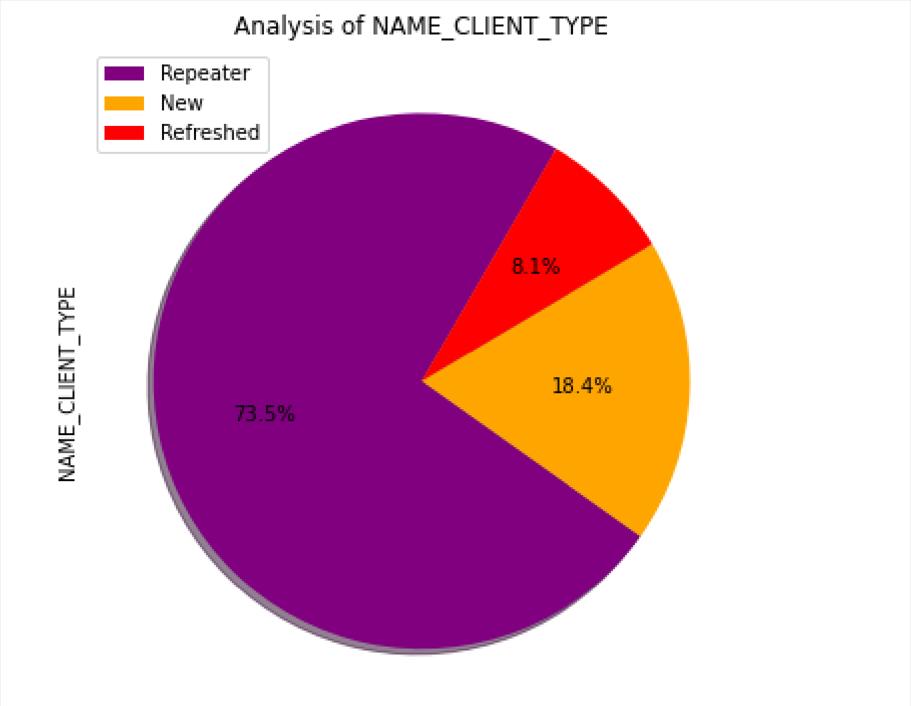


Univariate analysis of categorical variables



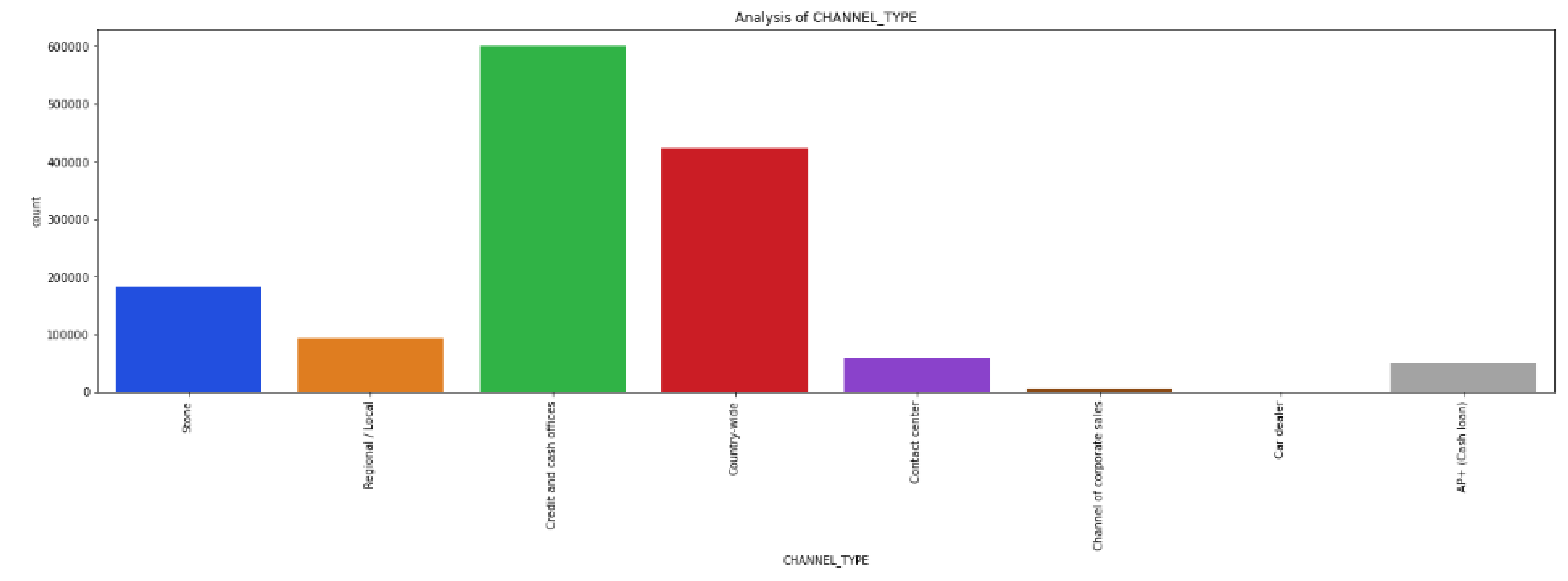
Analysis of `NAME_CONTRACT_STATUS`

- - `Approved` loan status is the highest among all loan applications
- - `Canceled` loan status is the second highest among all loan applications



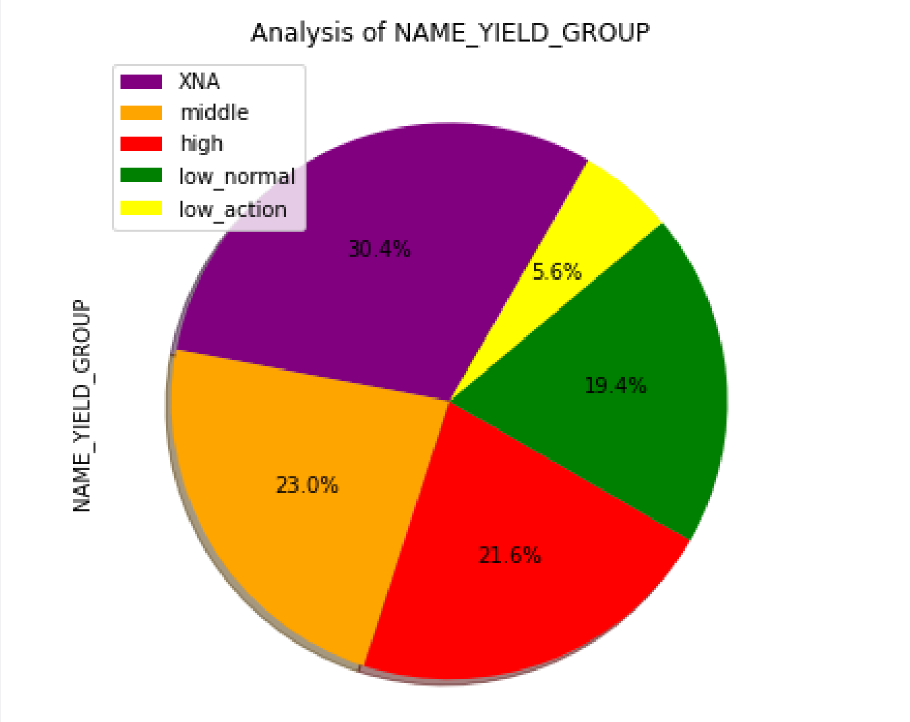
Analysis of `NAME_CLIENT_TYPE`

- - `Repeater` client type is the highest among all loan applications
- - `New` client type is the second highest among all loan applications



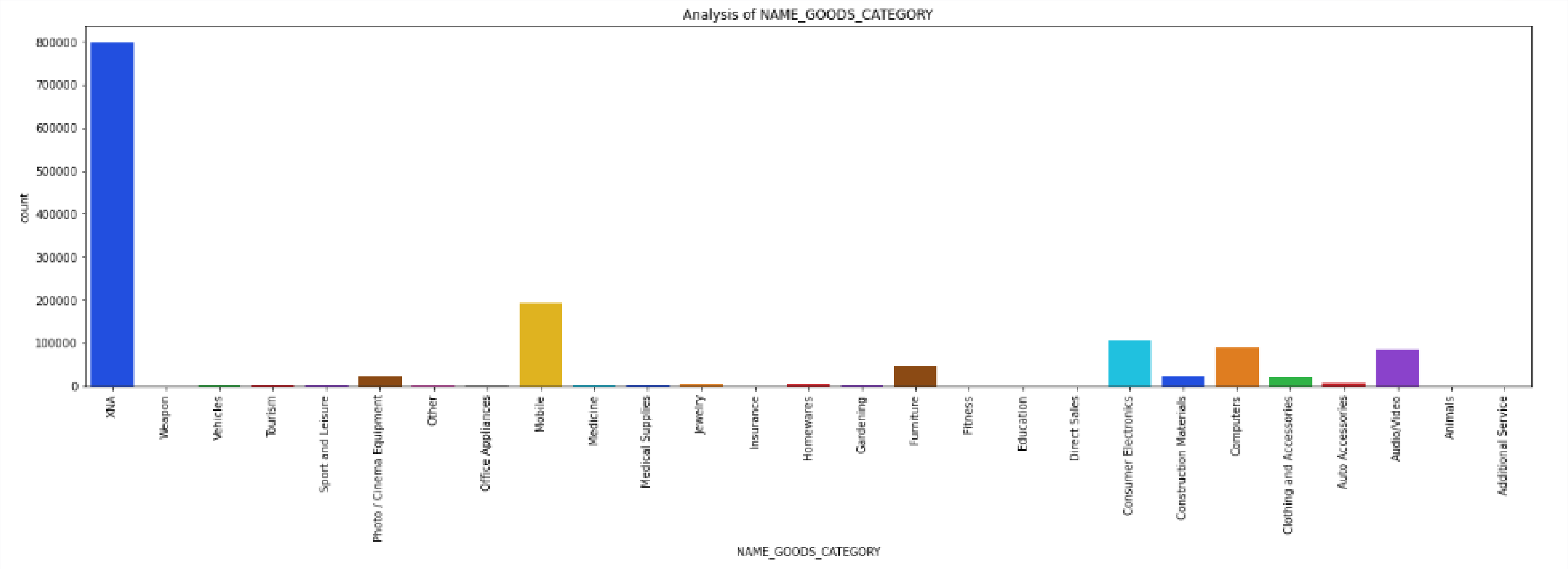
Analysis of `CHANNEL_TYPE`

- - `Country-wide` Channel type is the highest among all loan applications
- - `Credit and cash offices` is the second highest Channel Type among all loan applications



Analysis of `NAME_YIELD_GROUP`

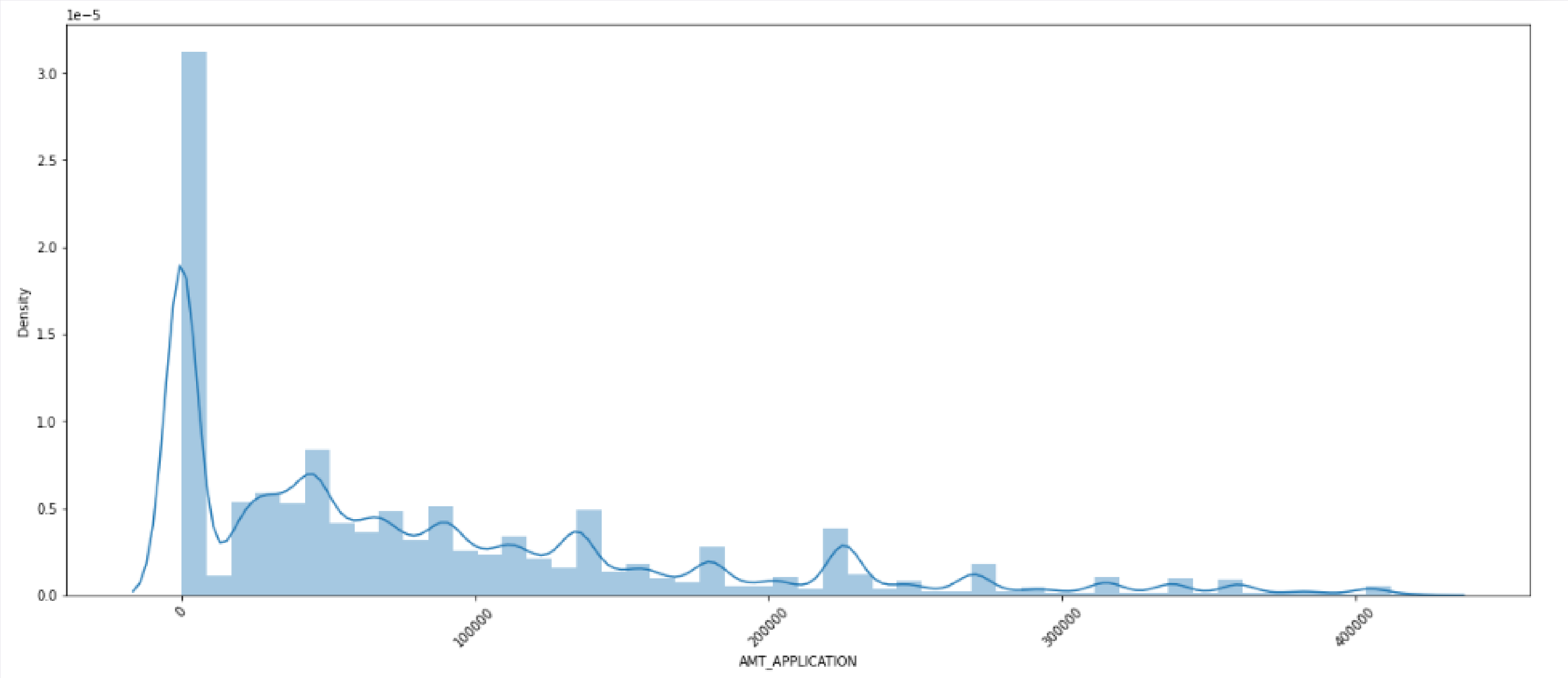
- - `XNA` interest rate is the highest among all loan applications
- - `middle` and `high` interest rates are the second and third highest among all loan applications



Analysis of `NAME_GOODS_CATEGORY`

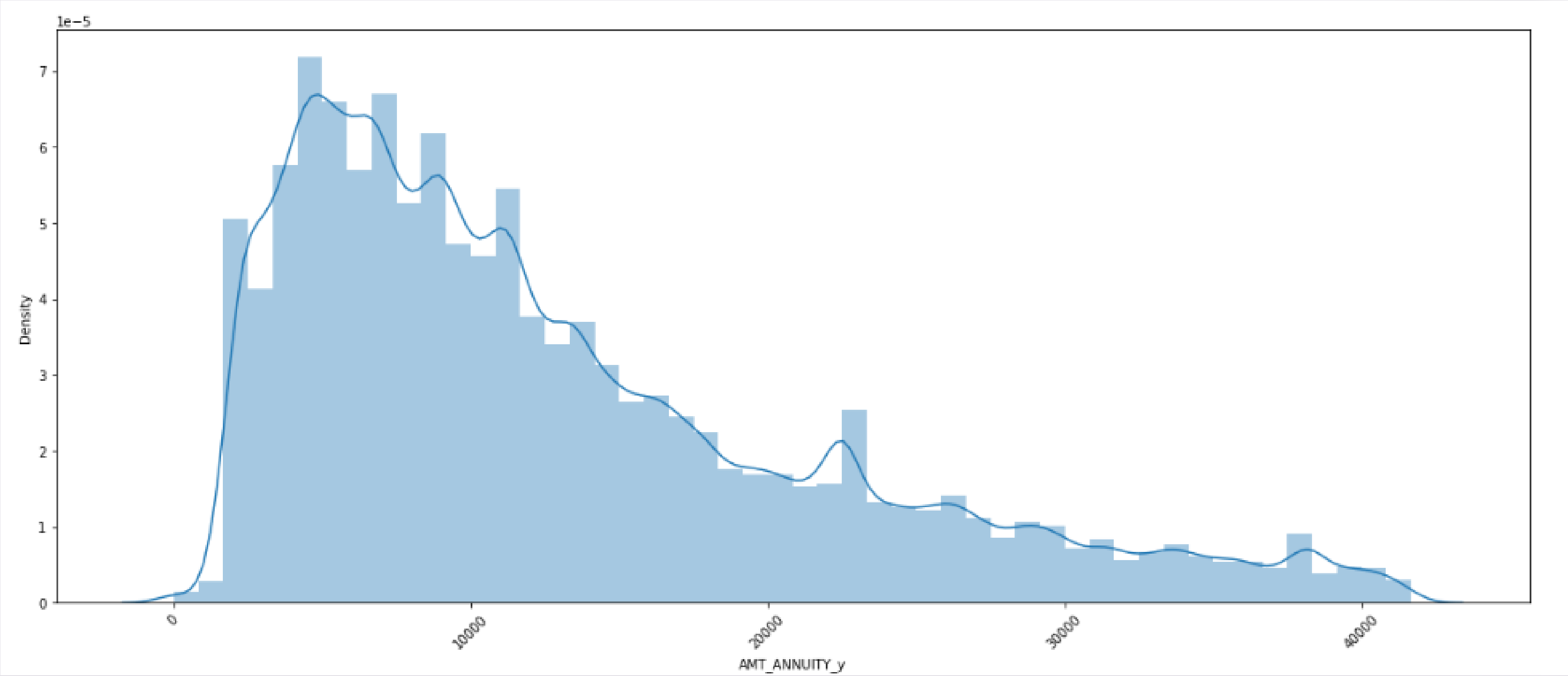
- - `XNA` goods category is the highest among all loan applications
- - `mobile` goods categoryis the second highest among all loan applications

Univariate analysis of numerical variables



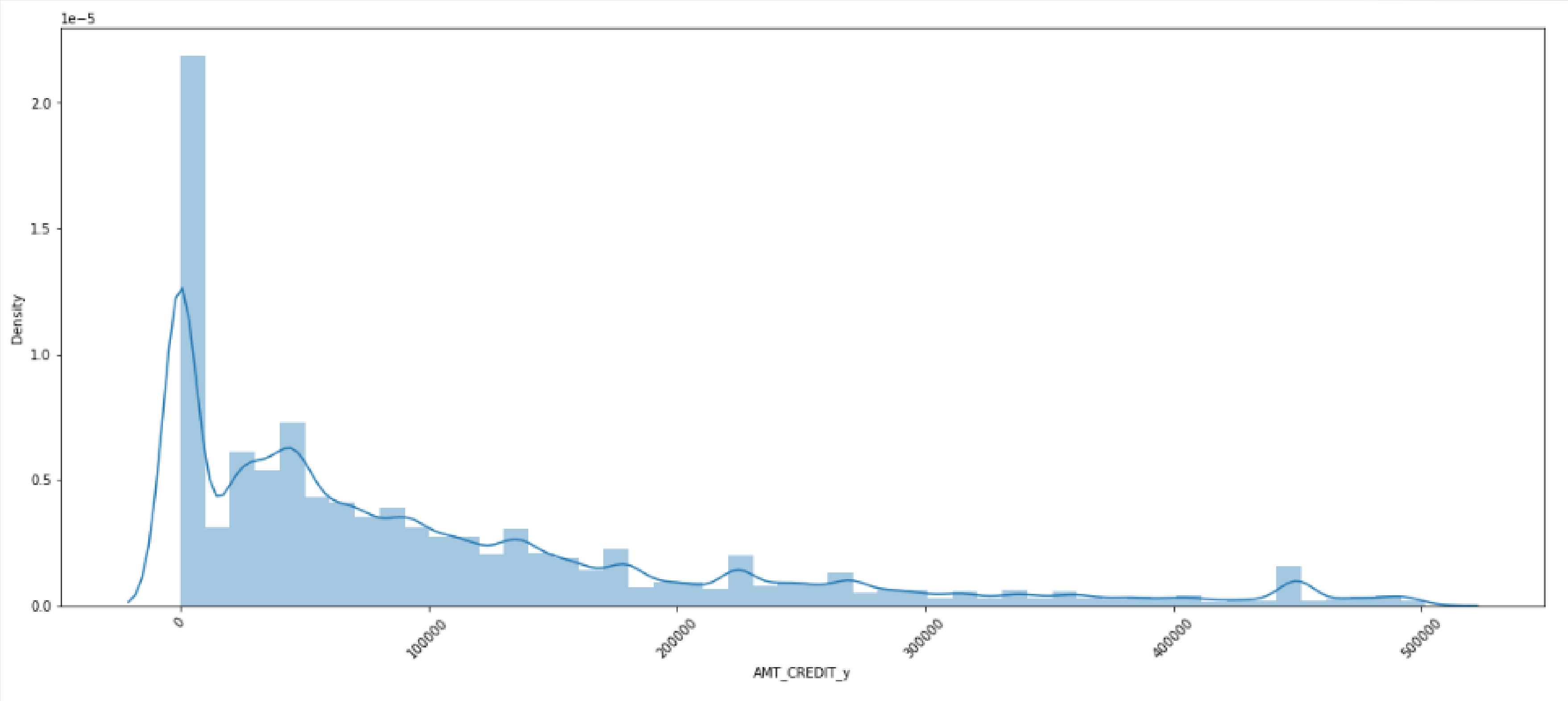
Analysis of `AMT_APPLICATION`

- - Most of the loan amount applied by the clients initially seems to be very small as can be seen from the huge spike at the beginning of the distribution



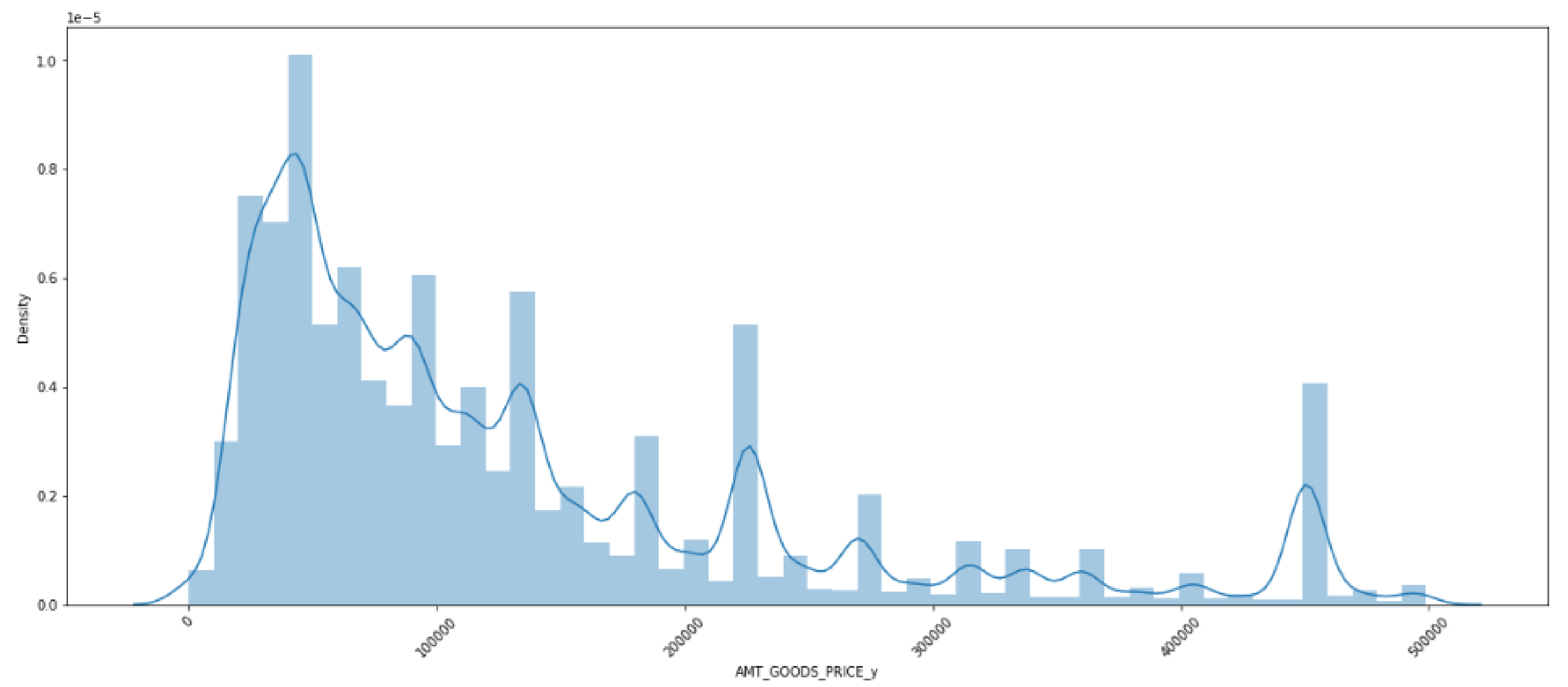
Analysis of \`AMT_ANNUITY_y\`

- \- Most of the previous loan's annuity from the clients is less than 10,000 as the distribution is high here
- \- As previous loan's annuity increases, the no. of clients decreases



Analysis of `AMT_CREDIT_y`

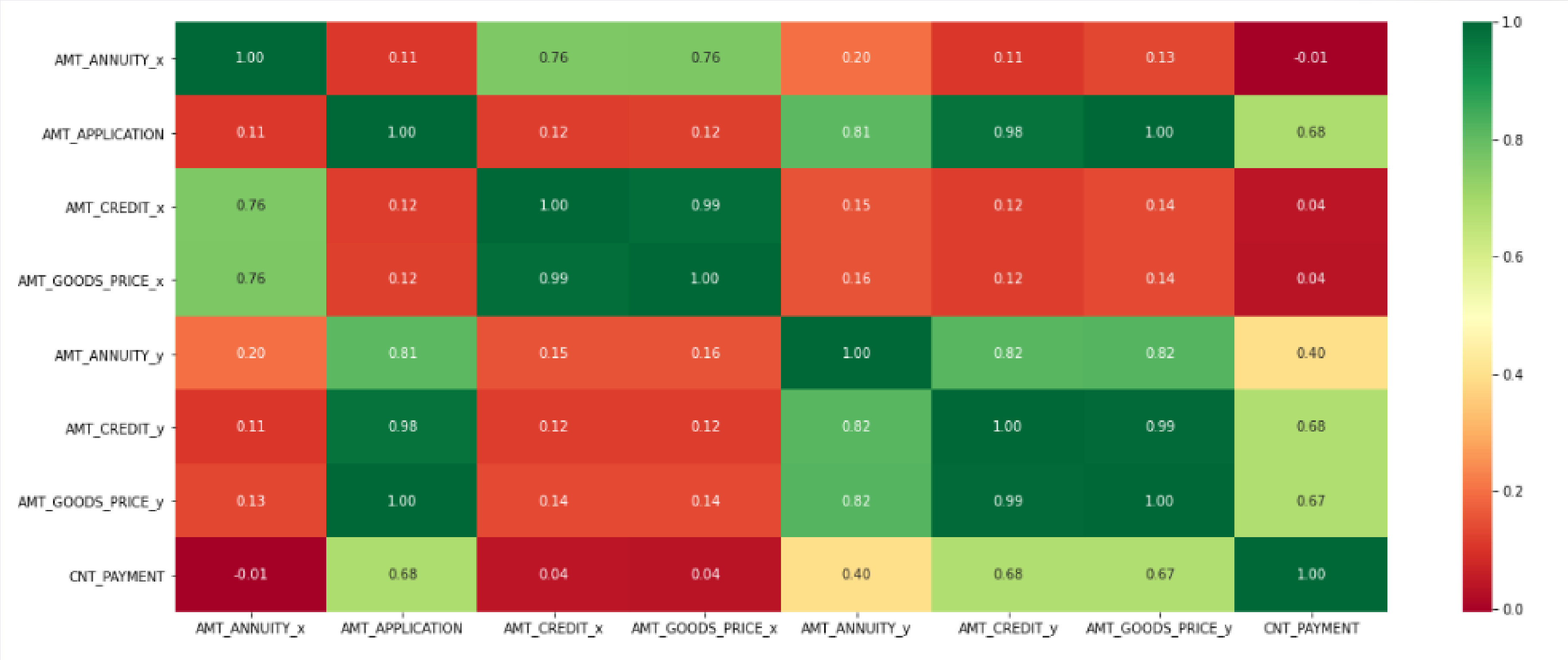
- - This distribution very closely resembles that of AMT_APPLICATION. This means that most people received the loan amount that they applied for



Analysis of `AMT_GOODS_PRICE_y`

- - Most of the goods price asked by clients in previous application is less than 100K

Correlation analysis of numerical variables

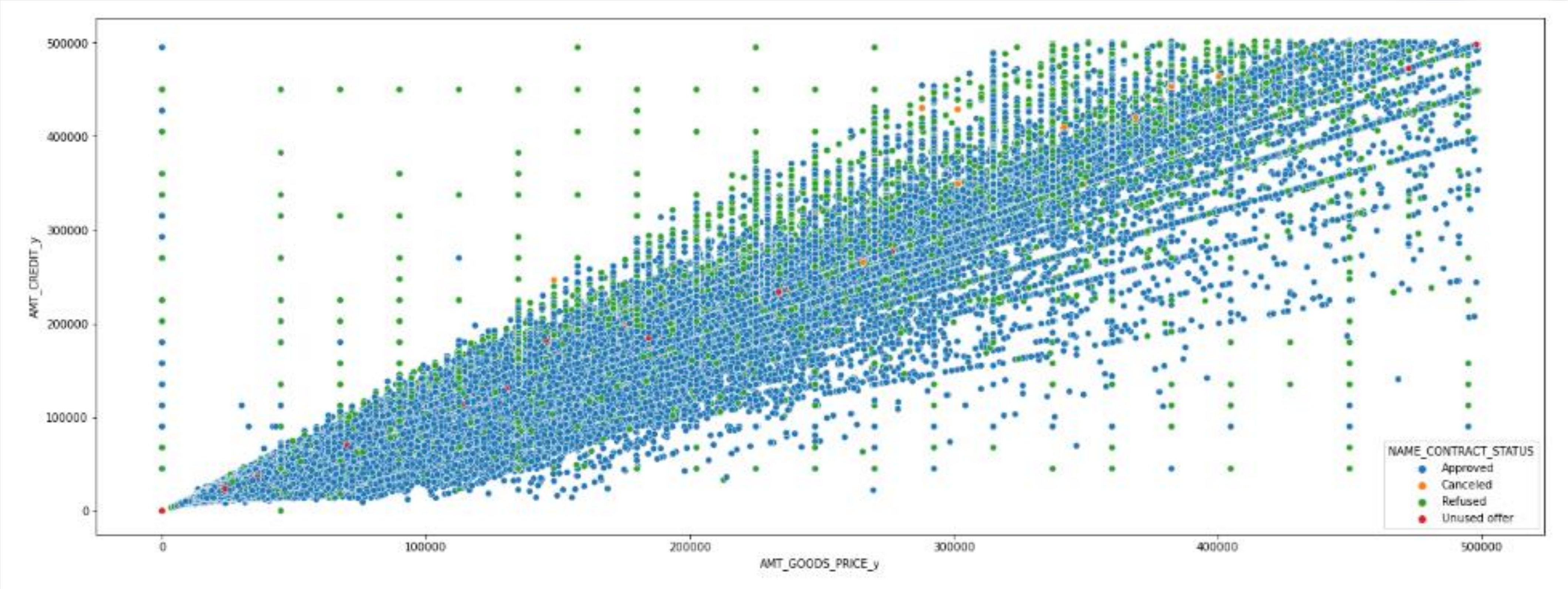


Correlation matrix

- - `AMT_APPLICATION` has a high correlation with `AMT_ANNUITY_y`, `AMT_CREDIT_y`, `AMT_GOODS_PRICE_y` and decent correlation with `CNT_PAYMENT`
- - `AMT_GOODS_PRICE_y` has a high correlation with `AMT_ANNUITY_y`, `AMT_CREDIT_y`, `AMT_APPLICATION` and decent correlation with `CNT_PAYMENT`
- - `AMT_CREDIT_y` has a high correlation with `AMT_GOODS_PRICE_y` and decent correlation with `CNT_PAYMENT`
- - `AMT_ANNUITY_x` has a high correlation with `AMT_GOODS_PRICE_y`, `AMT_CREDIT_y`
- - `AMT_ANNUITY_x` has a high correlation with `AMT_GOODS_PRICE_x`, `AMT_CREDIT_x`
- - `AMT_CREDIT_x` has a high correlation with `AMT_GOODS_PRICE_x`

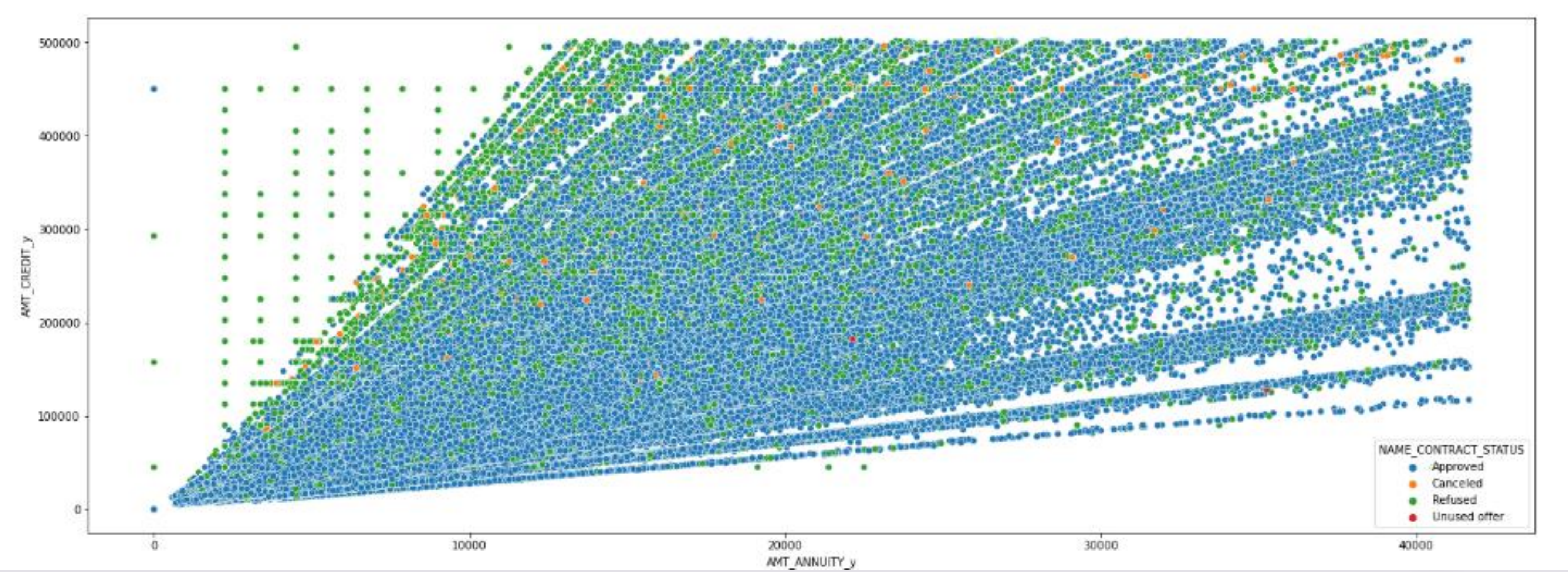
Bivariate/Multivariate analysis

Continuous V/S Continuous variables



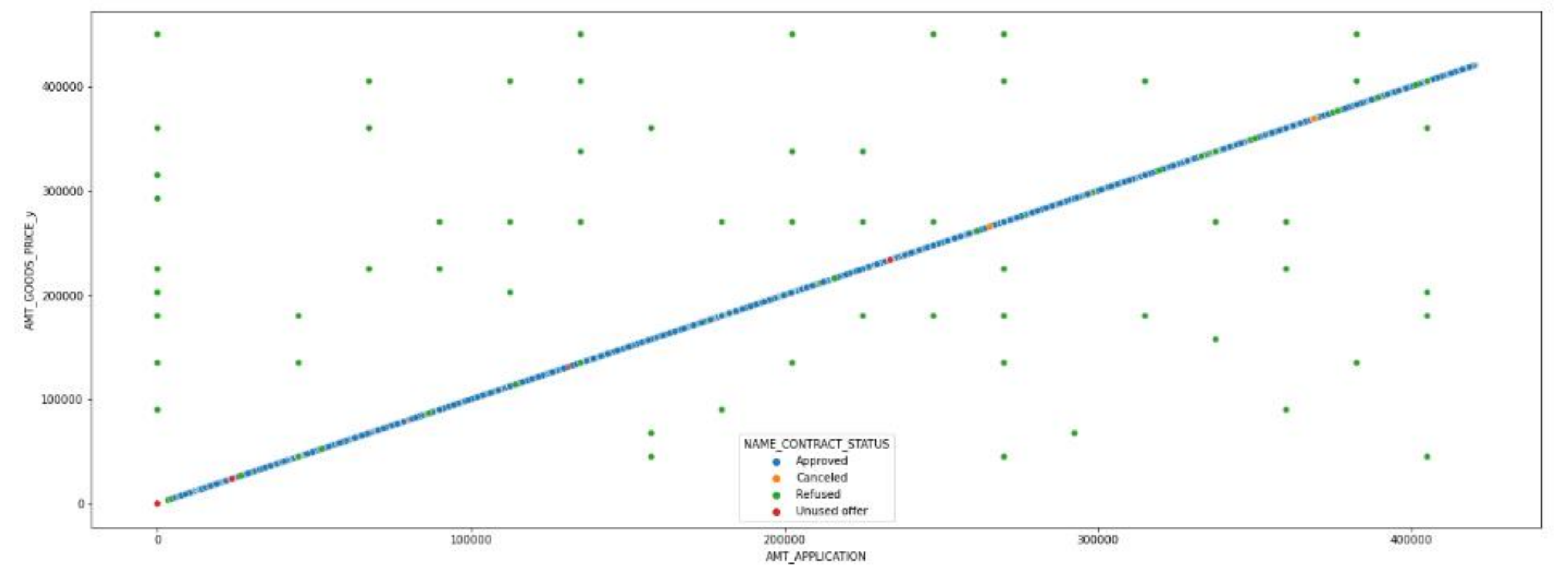
Analysis of \`AMT_GOODS_PRICE_y\` V/S \`AMT_CREDIT_y\` V/S \`NAME_CONTRACT_STATUS\`

- \- At lower levels of previous application's Goods price < 200K and Credit > 300k, have a chance of getting refused. However, this is a weak correlation as we have less data points to support this



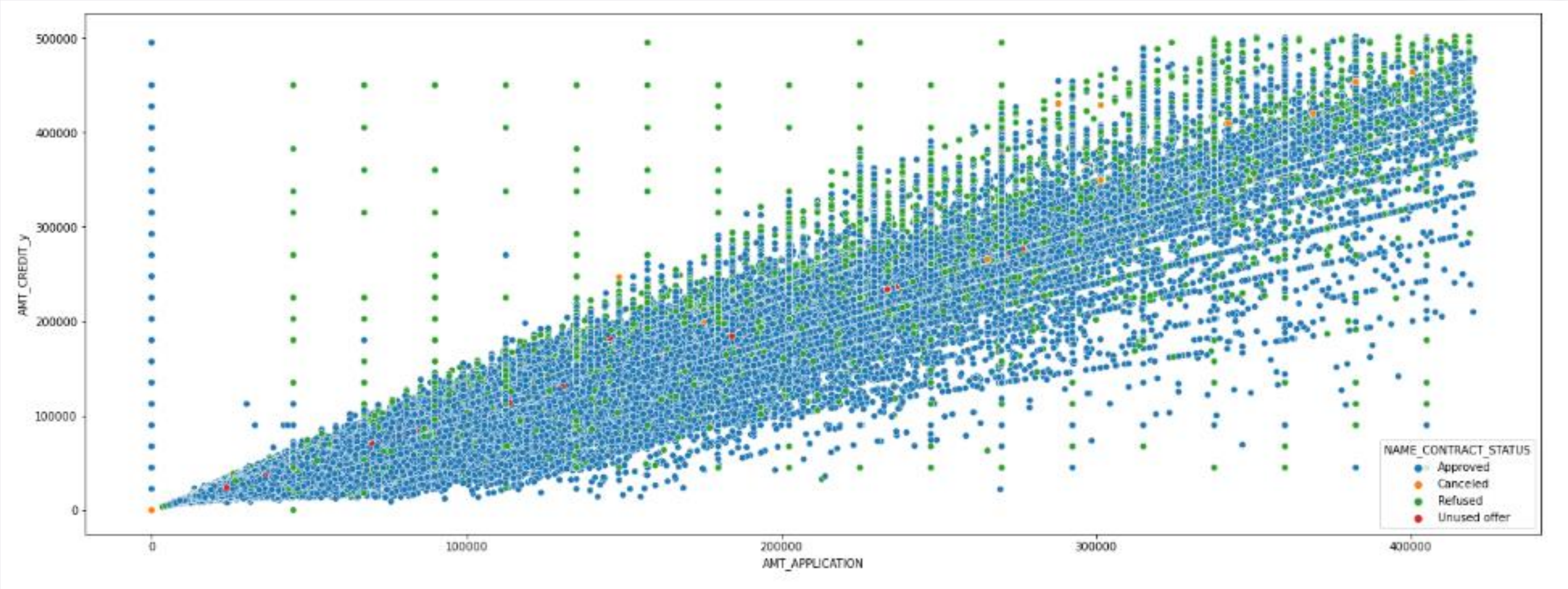
Analysis of `AMT_ANNUITY_y` V/S `AMT_CREDIT_y` V/S `NAME_CONTRACT_STATUS`

- - No correlations observed from scatterplot with respect to `NAME_CONTRACT_STATUS`
- - `AMT_ANNUITY_y` has a strong correlation with `AMT_CREDIT_y`



Analysis of `AMT_APPLICATION` V/S `AMT_GOODS_PRICE_y` V/S `NAME_CONTRACT_STATUS`

- - Application amount has strong positive correlation with Goods price

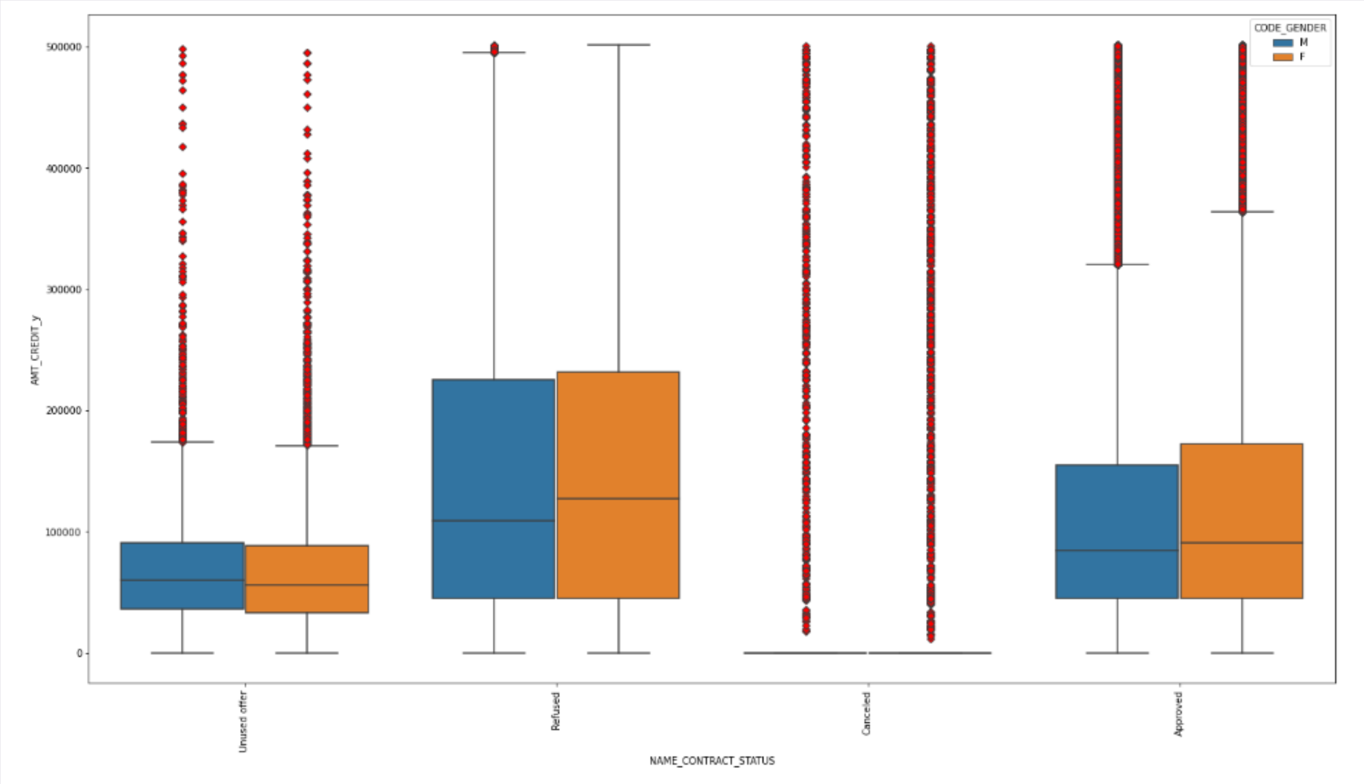


Analysis of `AMT_APPLICATION` V/S `AMT_CREDIT_y` V/S `NAME_CONTRACT_STATUS`

- - Application amount has strong positive correlation with Credit amount

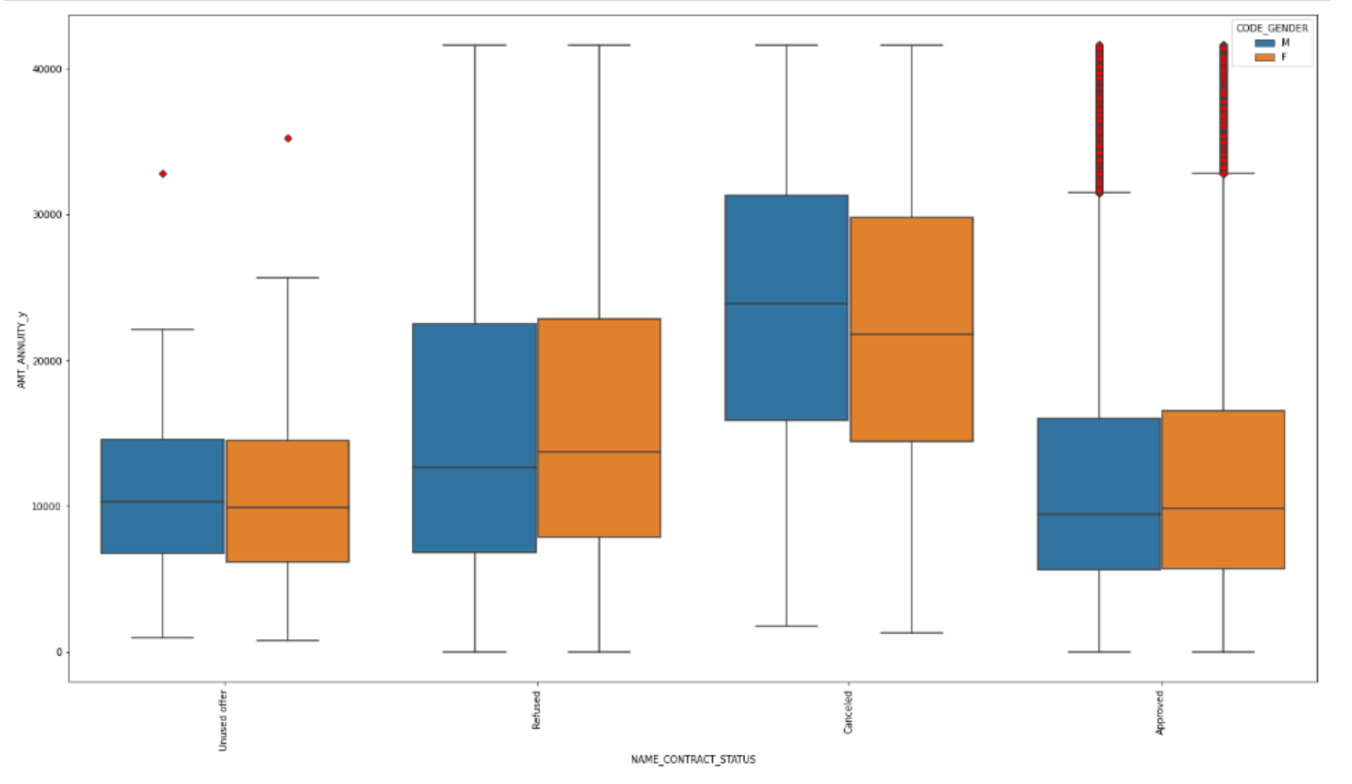
Bivariate/Multivariate analysis

Continuous V/S Categorical variables



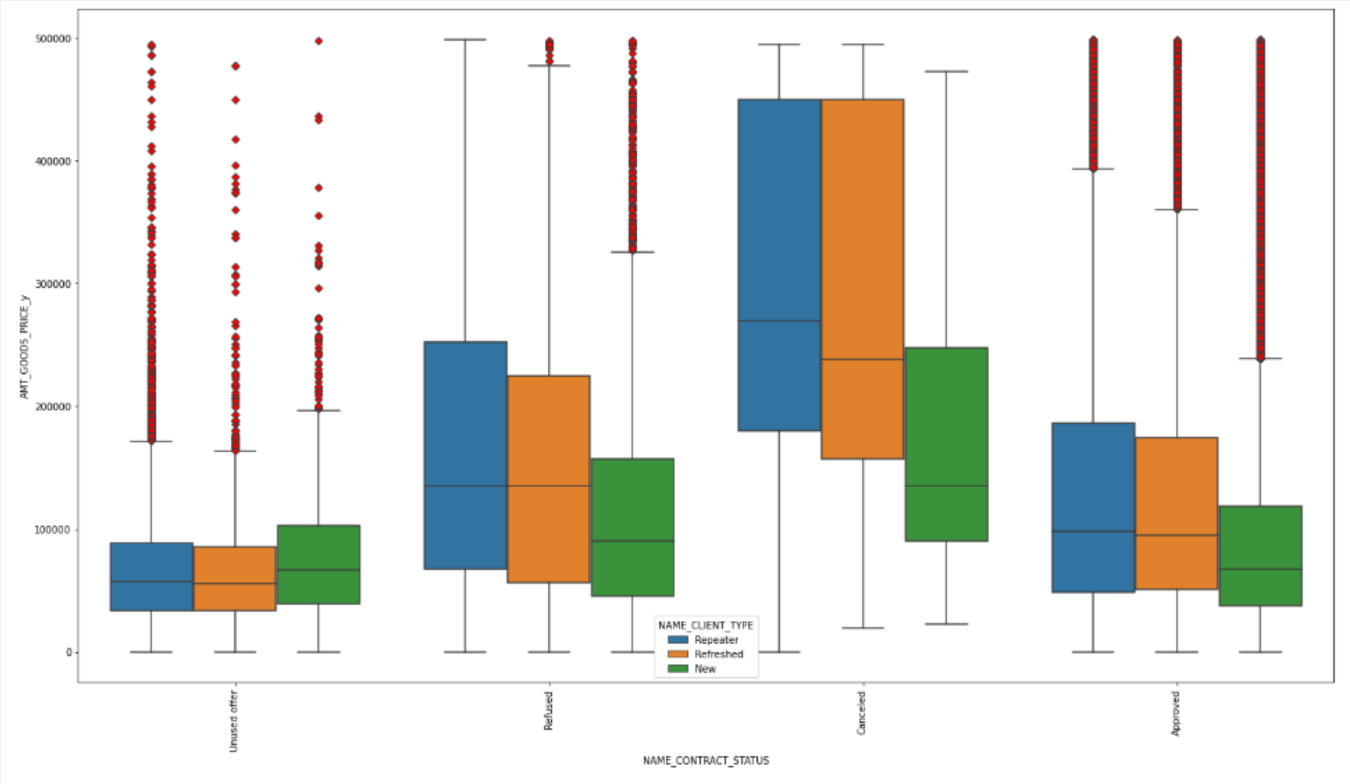
Analysis of `NAME_CONTRACT_STATUS` V/S `AMT_CREDIT_y` V/S `CODE_GENDER`

- - Clients who are `Refused` and `Female` apply for higher median credit amount than `Male`



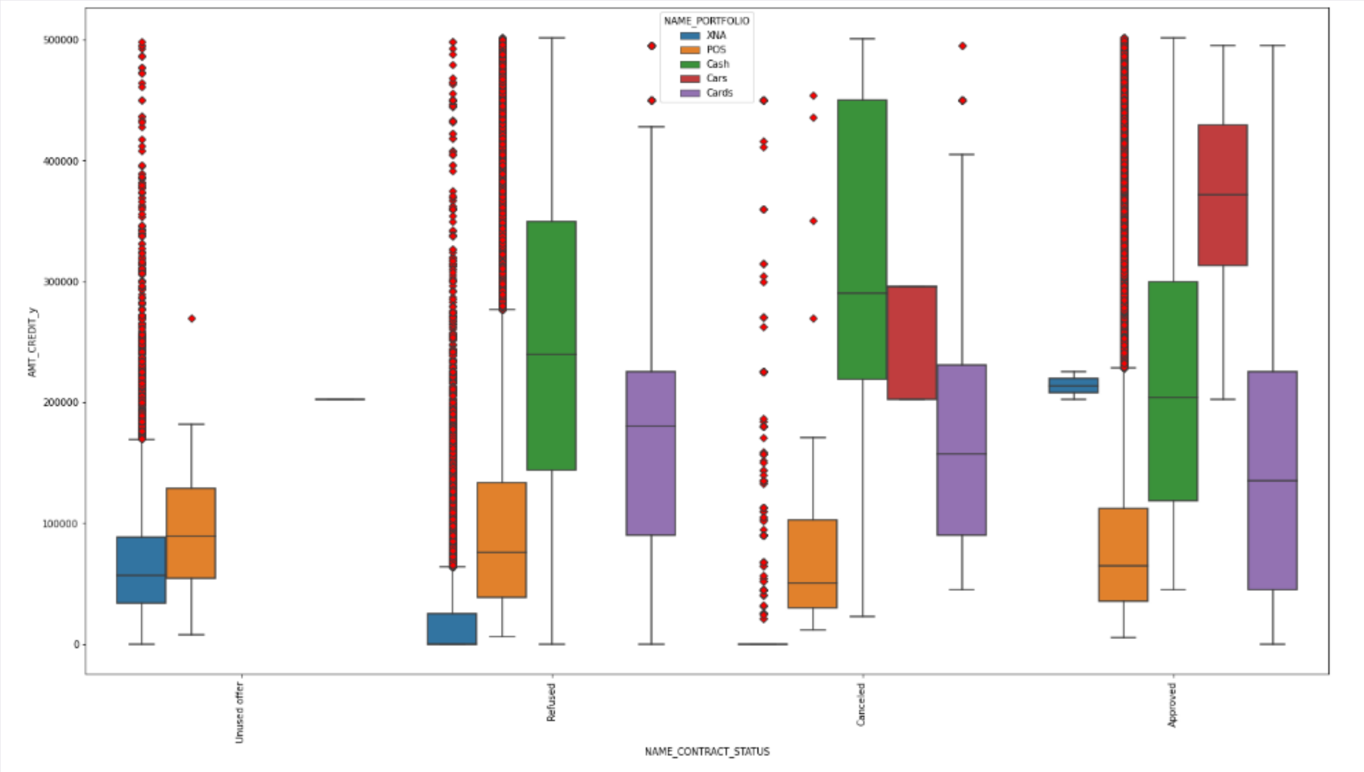
Analysis of `NAME_CONTRACT_STATUS` V/S `AMT_ANNUITY_y` V/S `CODE_GENDER`

- \- Clients who got `Cancelled` and `Male` paid higher median Annuity than `Female`
- \- Clients who got `Refused` and `Female` paid higher median Annuity than `Male`



Analysis of `NAME_CLIENT_TYPE` V/S `AMT_GOODS_PRICE_y` V/S `NAME_CONTRACT_STATUS`

- - Clients who are `New` and `Canceled`have less median goods price compared to `Repeater` and `Refreshed`
- - Clients who are `Approved` and `New` have less median goods price compared to `Repeater` and `Refreshed`

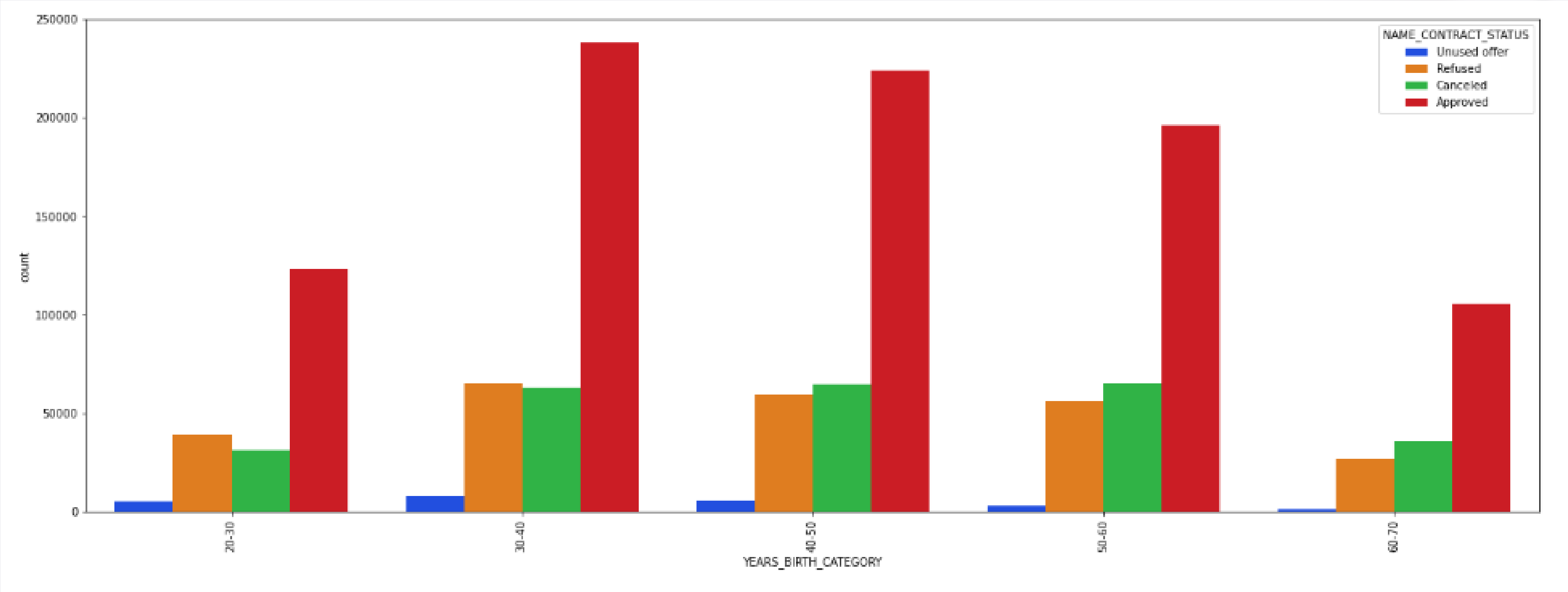


Analysis of \`NAME_CONTRACT_STATUS\` V/S \`AMT_CREDIT_y\` V/S \`NAME_PORTFOLIO\`

- \- Clients who have \`Unused offer\` receive more median credit in \`POS\` portfolio
- \- Clients who are \`Refused\` receive more median credit in \`Cash\` portfolio
- \- Clients who are \`Approved\` receive more median credit in \`Cars\` portfolio

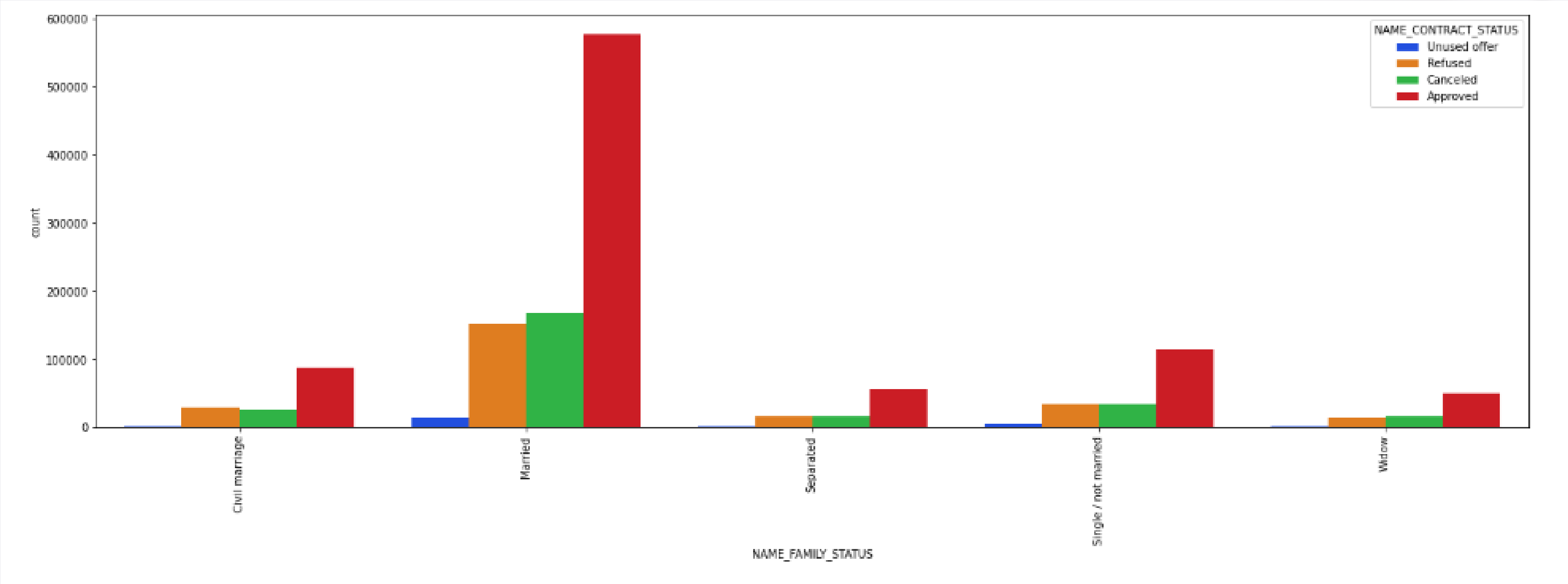
Bivariate/Multivariate analysis

Categorical V/S Categorical variables



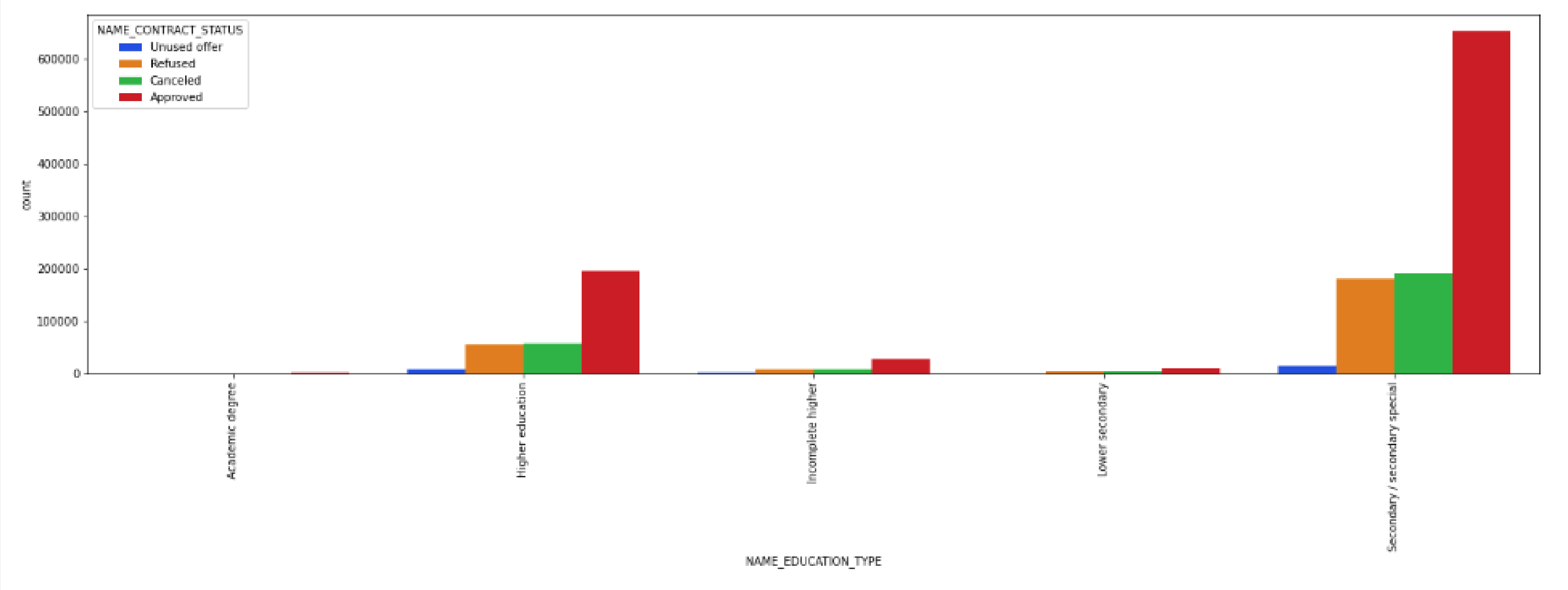
Analysis of \`YEARS_BIRTH_CATEGORY\` V/S \`NAME_CONTRACT_STATUS\`

- \- Clients who are in the age range 30-40 get most approval followed by clients in 40-50 age range
- \- Clients who are in the age range 60-70 receive least refusals followed by 20-30 age range



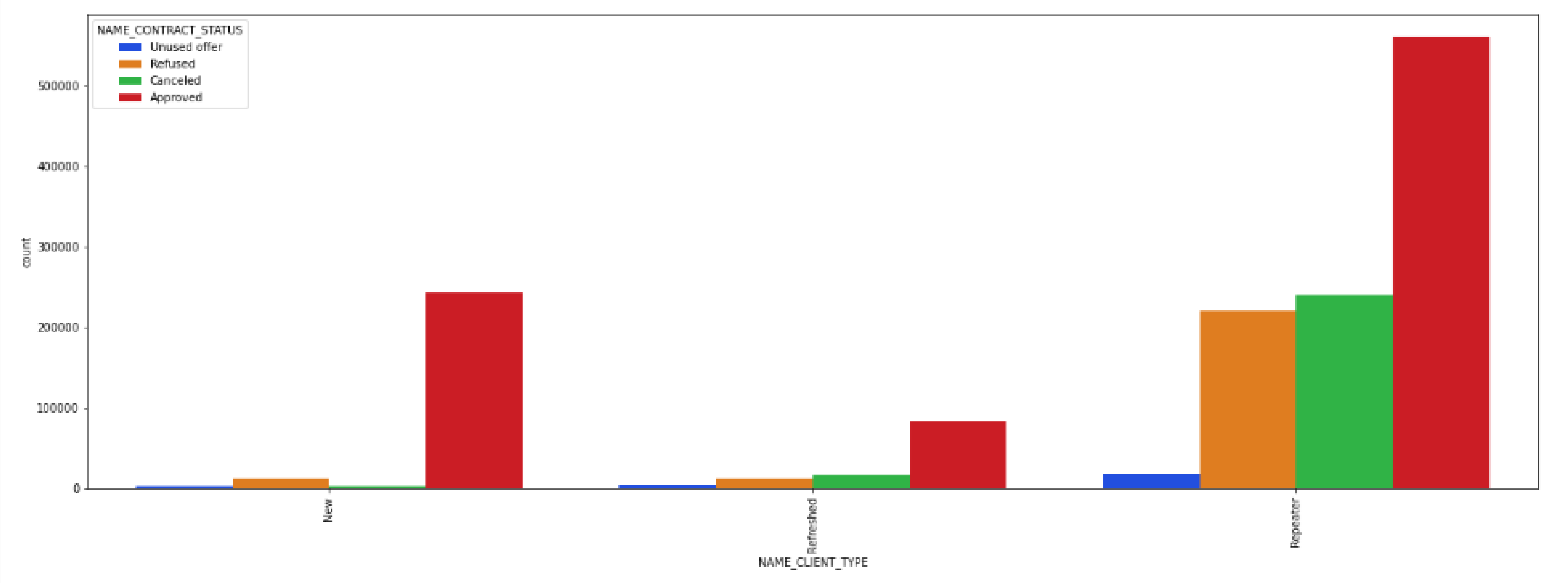
Analysis of `NAME_FAMILY_STATUS` V/S `NAME_CONTRACT_STATUS`

- - Clients who are `Married` receive the most approvals



Analysis of `NAME_EDUCATION_TYPE` V/S `NAME_CONTRACT_STATUS`

- \- Clients who have `Secondary/secondary special` receive the most approvals



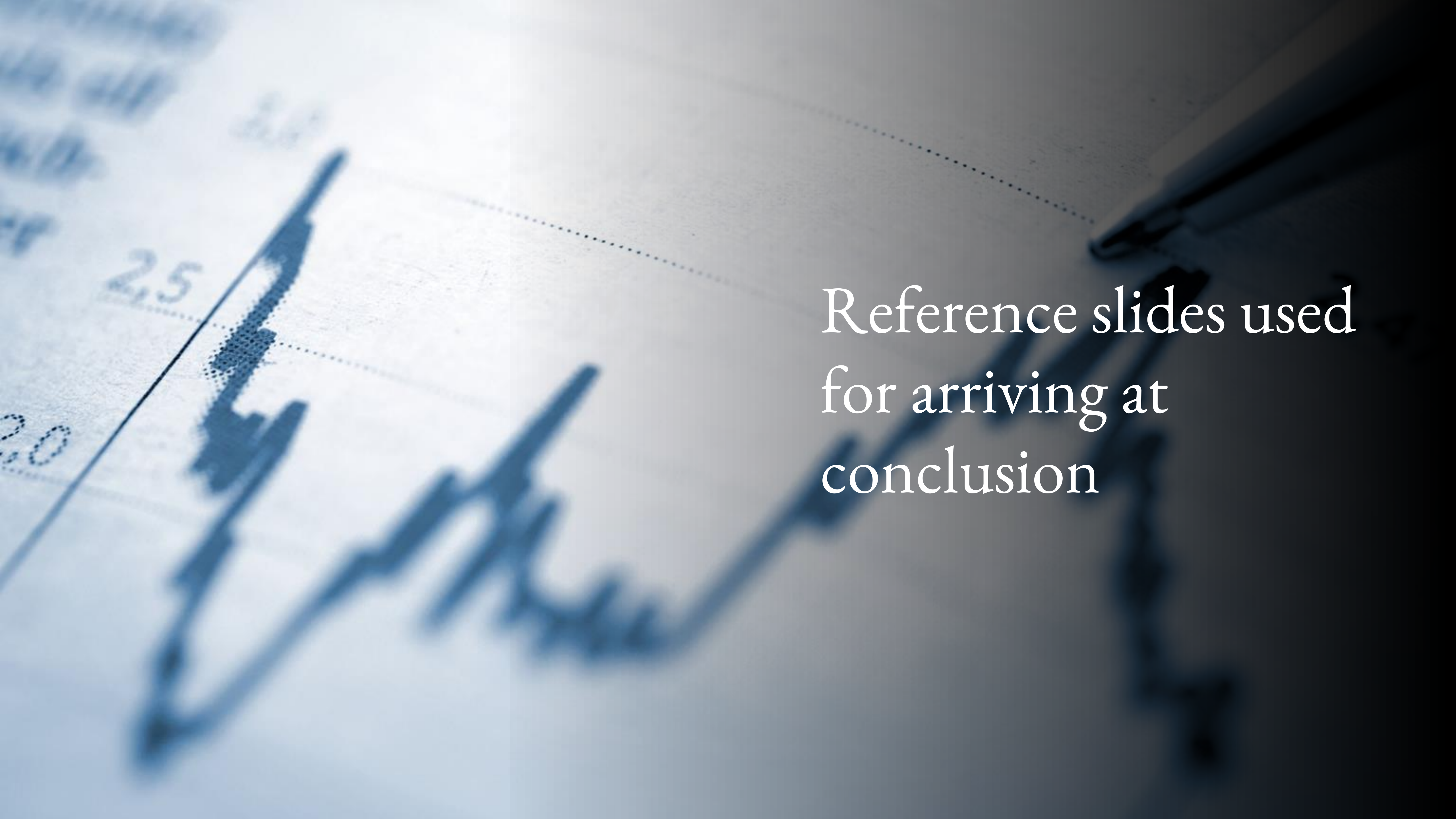
Analysis of `NAME_CLIENT_TYPE` V/S `NAME_CONTRACT_STATUS`

- - Clients who are `Repeaters` receive the most approvals followed by `New`

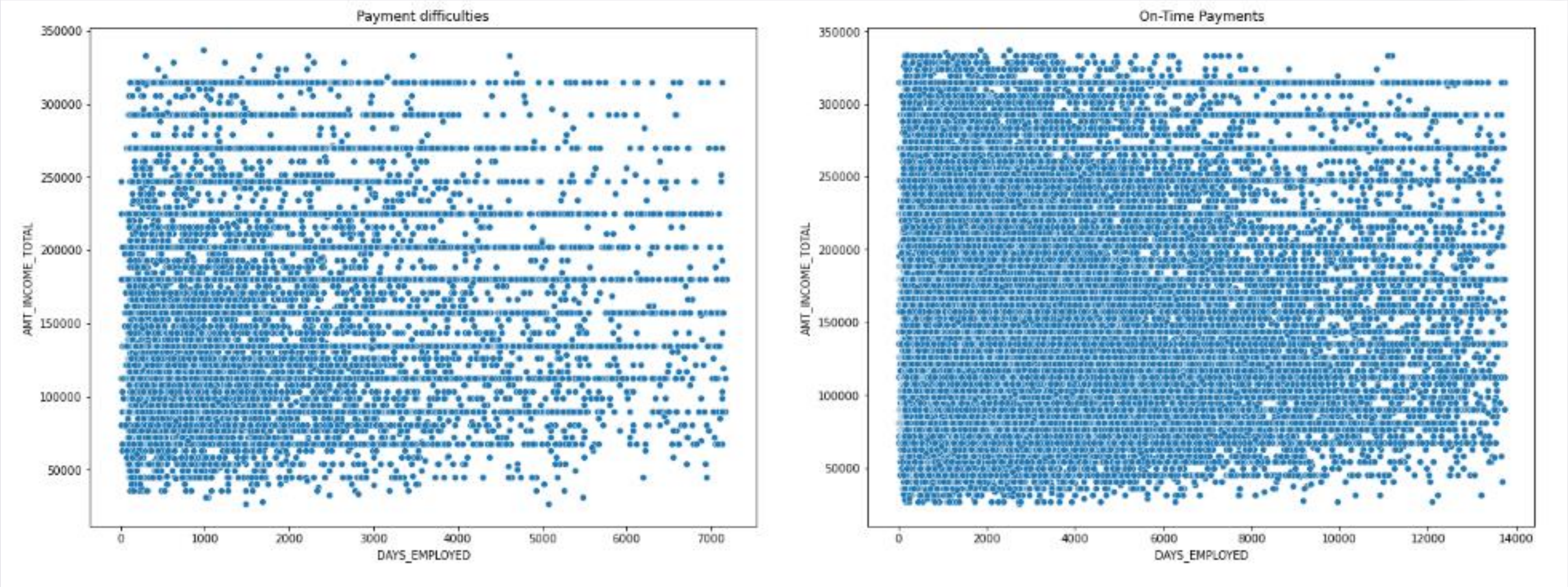
Conclusion

Client categories to be targeted for providing loan

- Clients who are employed for more than 19 years
- Clients in the age range 30-40 and 40-50
- Clients who are Married
- Male clients with Academic degree
- Students and Businessman
- Repeater clients

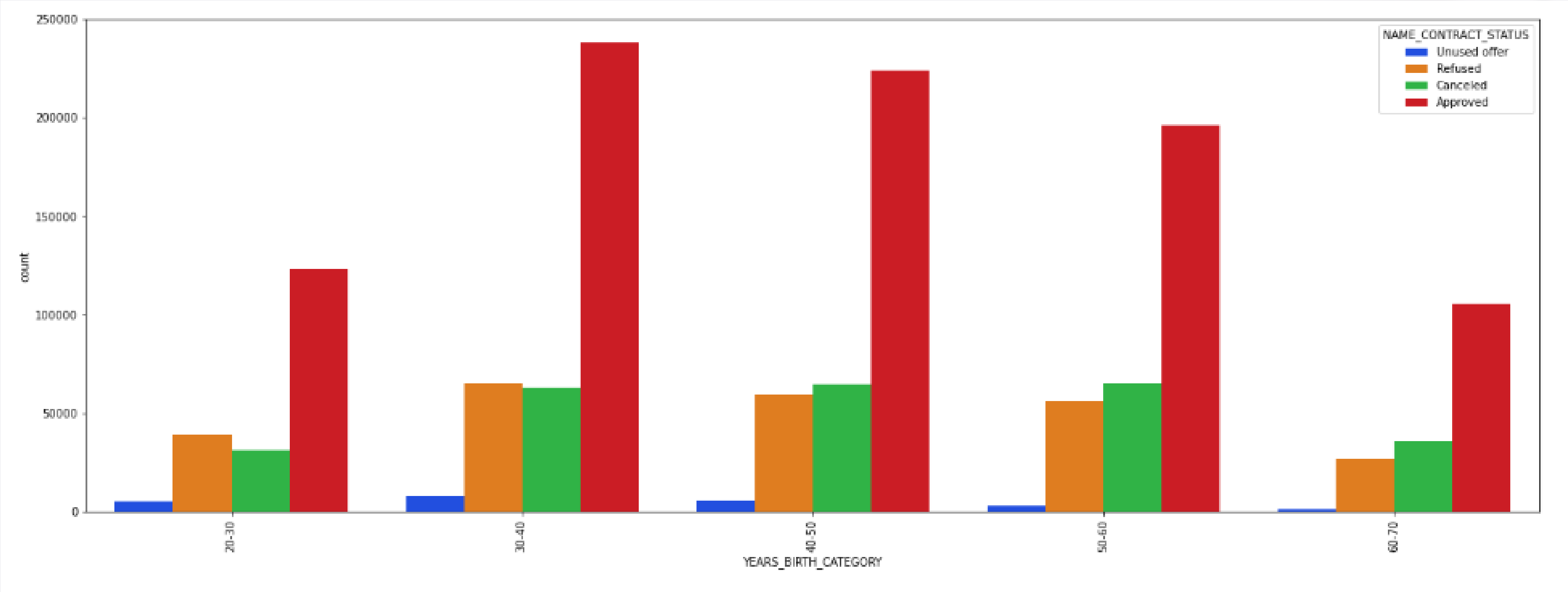


Reference slides used for arriving at conclusion



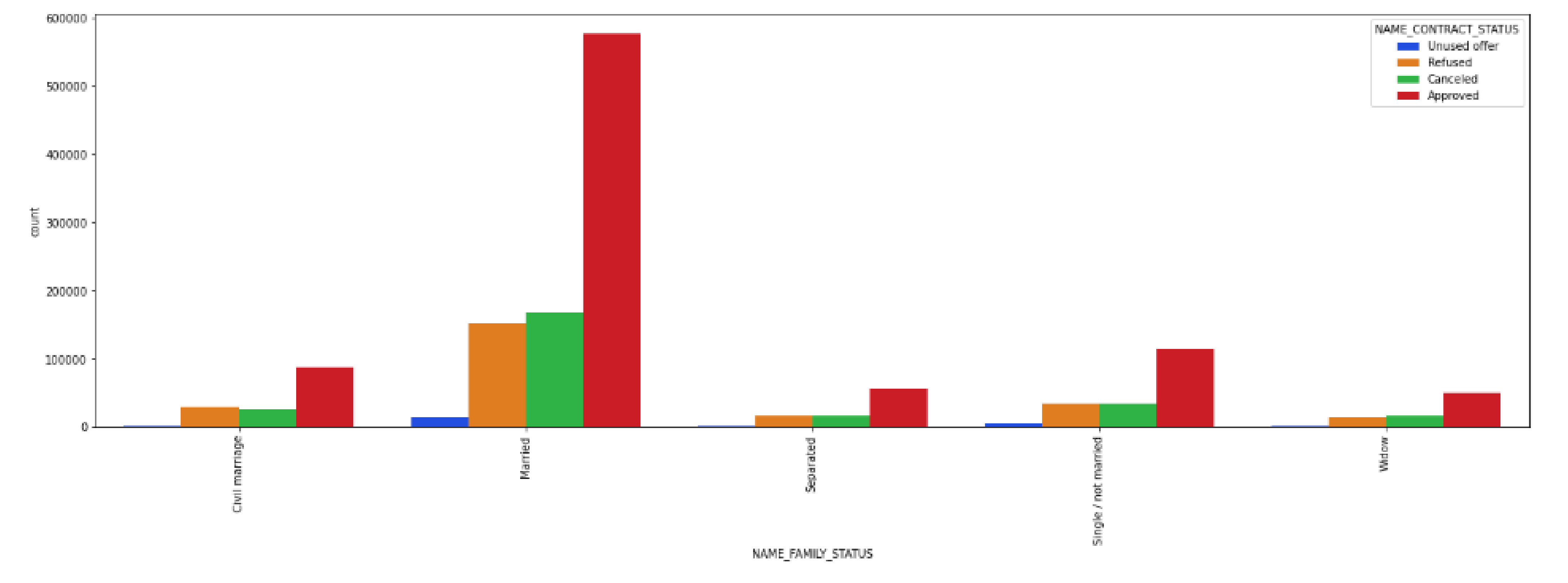
Analysis of `DAYS_EMPLOYED` V/S `AMT_INCOME_TOTAL`

- - Clients who are employed for a long time (>7000) days or 19 years are making their payments on-time but these category of clients do not exist in Payments difficulties group
- - Even looking at Payment difficulties group, clients with more than 4000 days of employment are sparse



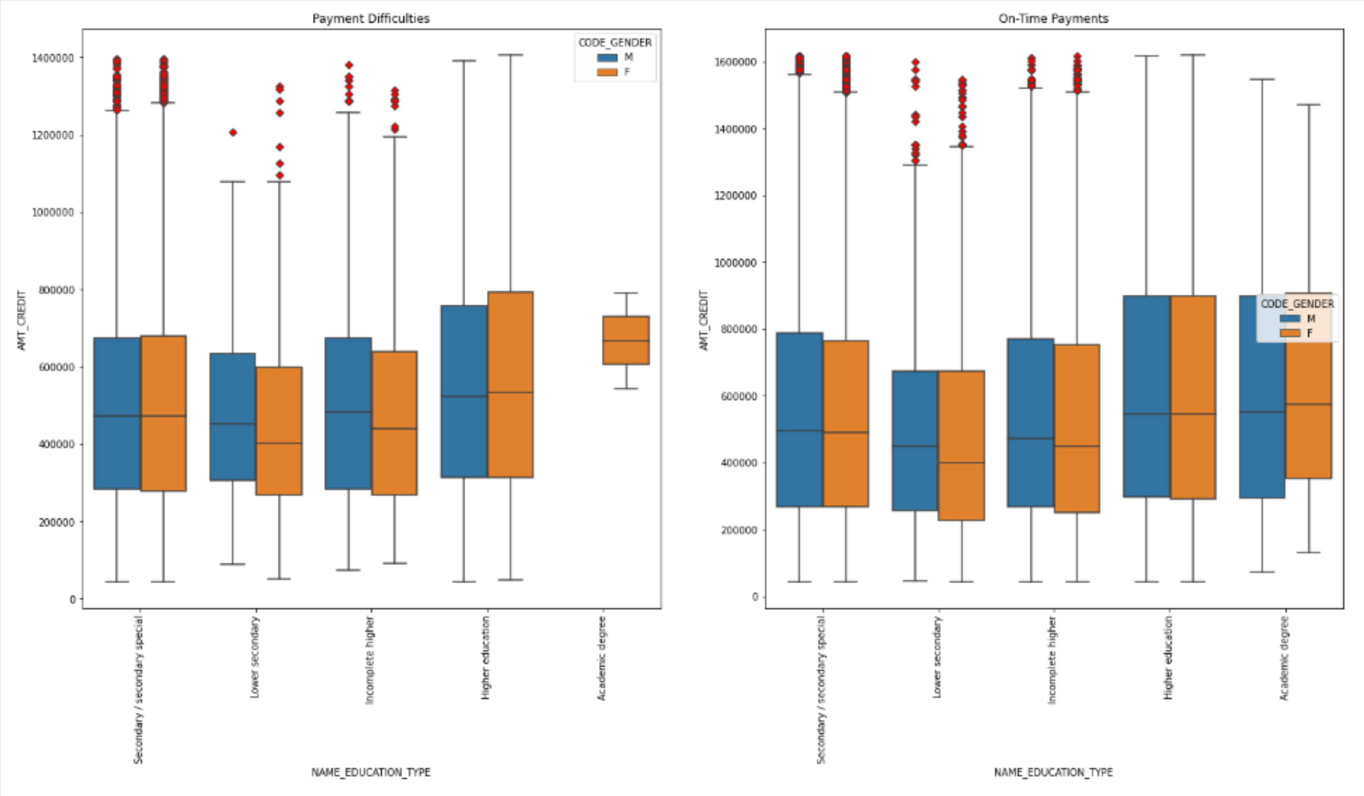
Analysis of \`YEARS_BIRTH_CATEGORY\` V/S \`NAME_CONTRACT_STATUS\`

- \- Clients who are in the age range 30-40 get most approval followed by clients in 40-50 age range
- \- Clients who are in the age range 60-70 receive least refusals followed by 20-30 age range



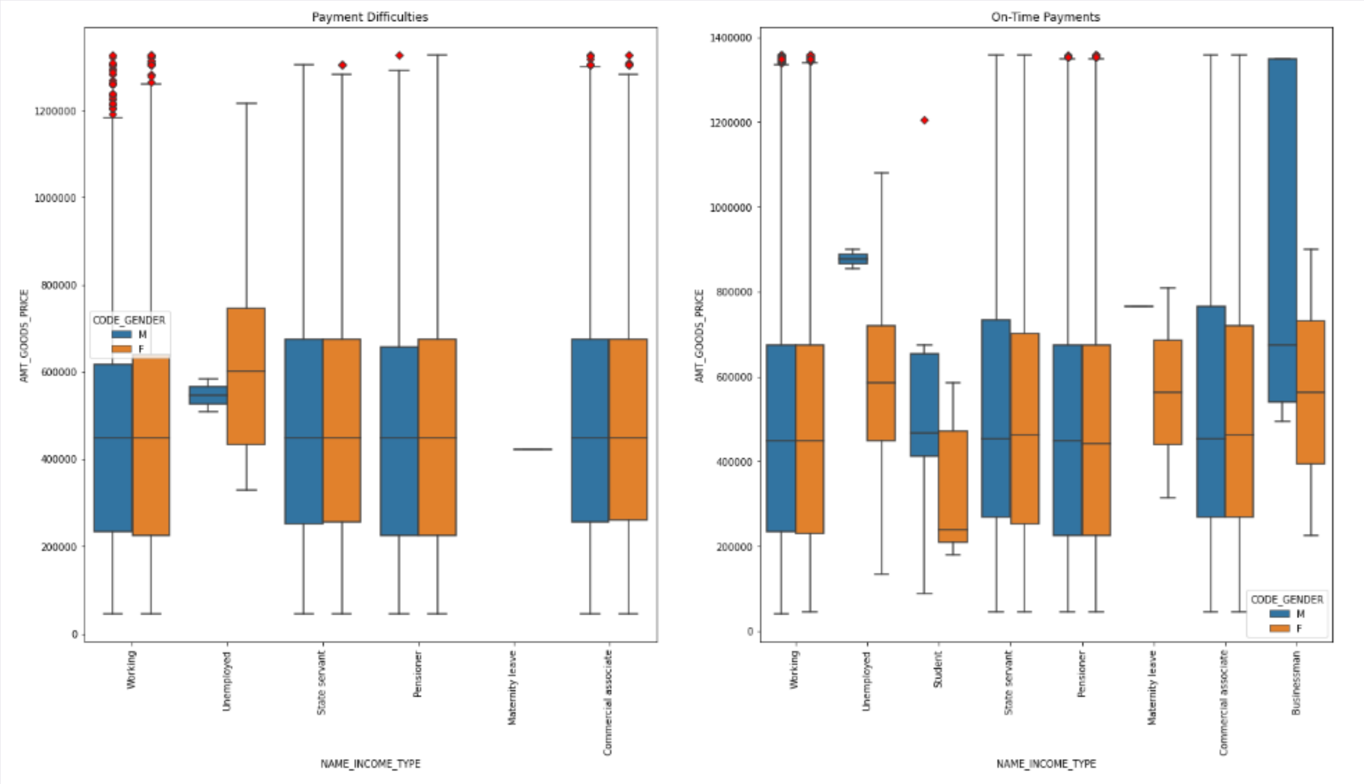
Analysis of `NAME_FAMILY_STATUS` V/S `NAME_CONTRACT_STATUS`

- - Clients who are `Married` receive the most approvals



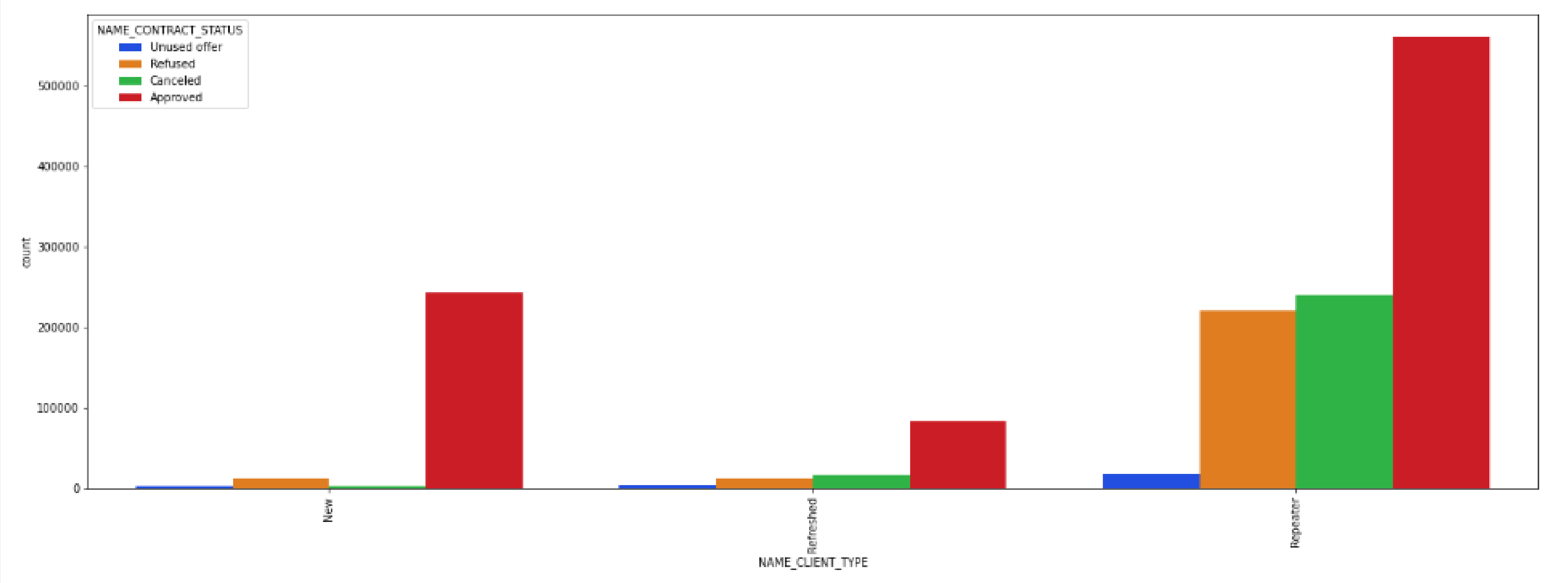
Analysis of `NAME_EDUCATION_TYPE` V/S `AMT_CREDIT` V/S `CODE_GENDER`

- \- Clients with `Academic Degree` have a wide range of credits for On-Time Payments whereas the range is much lower for ones with Payment difficulties
- \- Looking at summary statistics, Clients with `Academic Degree` and Payment difficulties take mean and median credit at a much higher range than On-Time Payment clients
- \- `Male` clients with `Academic Degree` always pay the loan on-time



Analysis of `NAME_INCOME_TYPE` V/S `AMT_GOODS_PRICE` V/S `CODE_GENDER`

- - Clients who are `Unemployed` and `Male` have a very high price of goods in On-Time Payments than Payment difficulties
- - Clients who are `Student` and either `Male` OR `Female` do their payments On-Time. They are completely missing from Payment difficulties category. `Student` seems to be an attractive category to give loans to.
- - Clients who are `Businessman` and either `Male` OR `Female` do their payments On-Time. They are completely missing from Payment difficulties category. `Businessman` seems to be an attractive category to give loans to.



Analysis of `NAME_CLIENT_TYPE` V/S `NAME_CONTRACT_STATUS`

- - Clients who are `Repeaters` receive the most approvals followed by `New`